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Wave energy converter array optimization: A genetic algorithm approach and minimum separation distance study

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ABSTRACT

With the need to integrate renewable energy sources into the current energy portfolio and the proximity of power consumers to ocean coastlines, it is important to evaluate marine energy systems, specifically wave energy converters (WECs), as potential solutions for meeting electricity needs. The ability to model these systems computationally is vital to their eventual deployment. The power development, economics, grid integration requirements, operations and maintenance requirements, and ecological impacts must be understood before these devices are physically installed. However, the research area of WEC array optimization is young, and the few available results of previously implemented optimization methods are preliminary. The purpose of this work is to introduce a new WEC array optimization framework to explore systems-level concerns, specifically WEC layout and device spacing. A genetic algorithm approach that utilizes an analytical hydrodynamic model and includes an array cost model is presented, and the resulting optimal layouts for a preliminary test case are discussed. This initial work is integral in providing an understanding of device layout and spacing and is a foundational starting point for subsequent and more advanced WEC array optimization research.

1. Introduction

As demand for electricity changes, and as communities seek to continually improve the quality of life and affluence of the growing population, the development and optimization of new, clean energy sources is of paramount importance. Of potential sources, ocean waves have a vast amount of energy and, for the last few decades, research and development regarding the harnessing of this energy has been ongoing. However, the economics of developing, implementing and maintaining wave energy converters (WECs) is lacking – particularly considering sea state volatility over the lifetime of WECs. As the industry moves towards ocean deployment of full-scale grid-connected WECs, an *a priori* optimization of the theoretical power system – including contributing factors such as power development, cost, and system parameters – is required, especially when demonstrating viability to stakeholders.

Current WEC array layout research considers only array power development, resulting in a lack of realism that precludes application of these approaches in deployment situations by offshore energy developers (Fitzgerald and Thomas, 2007; Bellew et al., 2009; Snyder and Moarefdoost, 2014; Ricci et al., 2007; Child and Venugopal, 2010; Child et al., 2011). The primary information missing from current WEC array optimization work is array economics; however, at this early stage of development, there is limited information about the various costs of WEC arrays. Despite this current limitation, it is important that any WEC array optimization framework incorporates cost modeling that can be updated as such information becomes available and accuracy improves.

This article presents a means of finding a WEC array configuration that optimizes conflicting objectives using a genetic algorithm optimization method. First, we will discuss previous approaches that have been used to generate WEC array layouts, followed by a discussion of our developed optimization method (a genetic algorithm approach). Next the objective formulations of cost and power will be presented. Finally, initial results of a preliminary WEC array optimization study using a binary genetic algorithm will be shown involving five devices in a random unidirectional sea state. Since our previous work explores the inclusion of array economics in a binary genetic algorithm (GA) to generate optimal layouts (Sharp and DuPont, 2015a, 2015b), the work presented here further investigates the significance of adjusting the prescribed minimum separation distance on an array's interaction factor as well as comparing the results with those of existing research.

2. Previous approaches

Much of the research in WEC array configuration draws upon lessons learned from the wind industry, particularly the effect of a device

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on its neighbors. However, unlike wind turbines, where nearby devices negatively affect the power production of surrounding turbines, WEC interactions have the capability to increase the electricity produced by an array (McNatt et al., 2014; Wolgamot et al., 2012). Achieving an interaction factor, q, greater than one has been the driving goal of current array optimization work; this demonstrates that array power production is greater than the power produced by the same number of devices acting in isolation (Weller et al., 2010; Borgarino et al., 2011; Goteman et al., 2015). Babarit investigates the interaction factor between single pairs of devices and arrays of devices, noting that while it is possible to achieve positive interaction factors in regular waves, the introduction of irregular waves limits this possibility. The potential for negative interaction between devices in tightly spaced arrays is discussed (Babarit, 2010, 2013). Weller et al. found that positive interaction between devices due to proximity are reduced with increasing significant wave height (Weller et al., 2010). Borgarino et al. suggests that the interaction between devices leads to triangular-shaped arrays achieving a greater value of q than square-based shapes due to masking (Borgarino et al., 2011). Göteman et al. looks at optimizing an array with a large number of devices. They note that arrays are important for limiting power output fluctuation and the clustering of point absorber type devices within an array will help with minimizing energy output variation (Goteman et al., 2015).

Without the use of optimization methods to better account for the factors influencing the configuration of a WEC array, many WEC layouts presented in previous literature have been chosen based on a researcher's educated judgment and then evaluated for power and interaction effects. As an example, Vicente et al. considers several configurations of WECs: single line, hexagonal, triangular, square and offset line (Vicente et al., 2013). Through evaluating these different arrangements and applying waves from different directions, the authors conclude that an increase in the interaction factor will not drive the design of array layouts, but rather factors such as cost and mooring will most influence layout configuration decisions. Additionally, Nambiar et al. utilized empirically-derived variations of radial layouts in the evaluation of cost associated with different electricity transmission options. However, while these works explored cost considerations of WEC arrays, the layouts presented were not explicitly optimized with cost as an objective function (Nambiar et al., 2015).

Introductory research has been conducted utilizing optimization methods for WEC layout design. McGuinness and Thomas implemented an analytical method to optimize the spacing between heave-constrained, spherical point absorbers that are in a line parallel to the oncoming wave (McGuinness and Thomas, 2015). However, it is challenging to include realistic complexities regarding device type and arrangement in a purely analytical method. In later work, they further explored the behavior of three devices in a line perpendicular to the incident wave and show the great variability that can come in power development based on a regular or an irregular sea state (Mcguinness et al., 2017). The initial, primary research used for array optimization comparison was conducted by Child and Venugopal (2010). They have presented two methods for optimizing WEC layouts – each considering five truncated WEC cylinders (similar to Fig. 8) vertically constrained to act in heave. The first method, parabolic intersection (PI), involved placing down-wave devices in the parabolic wake of the up-wave devices. Fig. 1a shows an example array achieved by this method. In addition to the parabolic intersection method, a genetic algorithm approach within MATLAB's Optimization Toolbox was used. This method, limited to 50 generations, achieved configurations such as the layout shown in Fig. 1b (Child and Venugopal, 2010). This baseline work allows for further exploration regarding implementing more advanced optimization techniques in WEC array design.

More recently, Wu et al. demonstrated an improvement in their optimization efficiency when considering a three-tether, submerged buoy array. A variation of an evolutionary algorithm and a covariance matrix adaption-based evolutionary strategy were both utilized. For this specific device type and single frequency, an interaction factor gain was shown that increases the speed of the optimization process (compared to their previous work) (Wu et al., 2016). Sarkar et al. have also completed work in array optimization - specifically of oscillating surge-type devices using machine learning and a genetic algorithm. They state that for these types of devices, clustering should be avoided, but that a positive interaction can be attained between the devices (Sarkar et al., 2016). Ferri considers a covariance matrix adaptation evolutionary strategy (CMA-ES) and a metamodel algorithm (MM) in order to compare computational expense and developed power. The MM is found to be able to converge rapidly, but was not accurate. Though, it could be potentially used as an initial step if paired with a more accurate method in a second phase (Ferri and Cork, 2017). Giassi et al. has also investigated the optimization of a WEC array where the diameter of the device and the gridded spacing of the devices was varied. The results indicate that the changing of a device's diameter primarily affects the cost of a device – not the power development of a device. However, varying the mass has a greater impact on the power developed (Giassi et al., 2017). Bozzi et al. considers annual energy production, hydrodynamic interaction and electrical interaction in connection with array configuration. Assuming a small array, they show that the optimum layouts for their experienced sea states are in the shape of a rhombus or a line (Bozzi et al., 2017).

The referenced work serves as a starting point for WEC array optimization research, and the goal of our current work is to expand the capability of WEC array optimization methods and to increase fidelity of models employed, specifically cost consideration and advanced input parameters. The following sections discuss our novel genetic algorithm approach for finding optimal WEC arrays, and show preliminary results using a similar problem formulation to that of Child and Venugopal (2010).

3. Genetic algorithm approach

We used a GA approach because of its ability to efficiently converge on optimal solutions while considering continuous and discrete factors. System optimization with GAs is not a new method; however, the application of such an optimization method in the realm of wave energy converter array design is novel. Additionally, our presented GA was developed specifically to be tuned for this challenge. Applications in the analogous field of wind energy turbine array optimization indicate the need for distinctively implemented algorithms (DuPont and Cagan, 2010). In this section we will give an overview of the workings of our GA – discussing the features that are uniquely important to our problem of optimizing an array of WECs within a binary grid.

To evaluate and compare different possible layouts, an objective function that includes both cost and power is created and utilized. The multi-objective formulation shown in Eq. (1) reflects the trade-off between cost and power as demonstrated by previous research (DuPont and Cagan, 2010; Mosetti et al., 1994; Grady et al., 2005).

$$\text{Objective Function} = \frac{\boldsymbol{Cost}}{\boldsymbol{P}_{20}} \tag{1}$$

In this objective function, the values of *Cost* and P_{20} represent the cost of and power generated by an array over a 20-year lifetime. Throughout the search, the objective function is minimized and the units are cents per kilowatt. As cost models achieve increased robustness, Eq. (1) could readily represent a lifetime-average cost of energy and could be used for comparing wave energy against sources such as wind or solar. For this specific study, the cost does not impact the layouts due to the simplicity of the cost model and the number of WECs being fixed. Unfortunately, current cost models do not exist that allow for greater fidelity when considering an array of devices. At this current stage of WEC array optimization research, we are considering a scenario that allows for better comparison with previous research – which only considers for a fixed number of devices. Fixing the number of devices allows us to

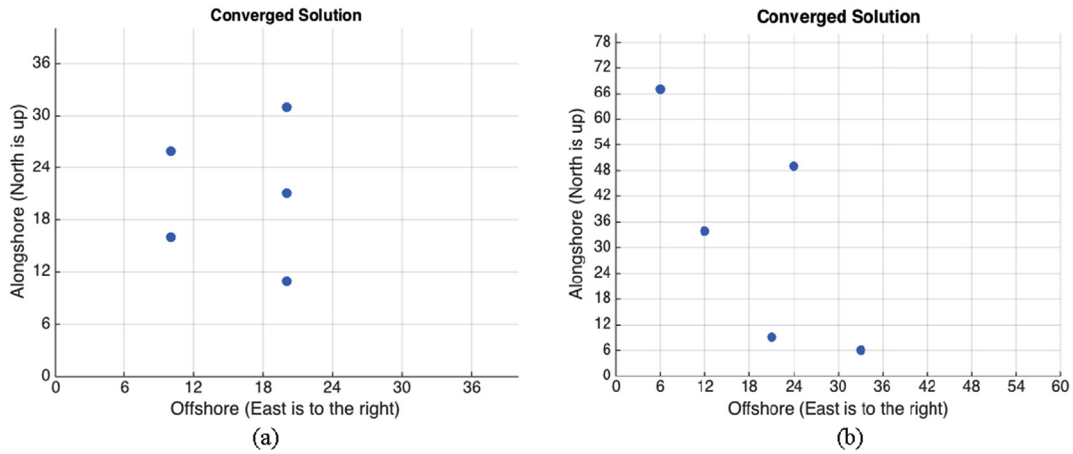

Fig. 1. Example arrays achieved using (a) parabolic intersectionand (b) MATLAB'S genetic algorithm toolbox (Child and Venugopal, 2010).

acquire a better understanding of other influencers on the configuration of WECs in an array. Inclusion of the cost in the objective function provides a placeholder for future implementation of improved cost models as they are developed.

As an evolutionary optimization algorithm, a GA mimics the passing of traits from parents to children, with mutations preventing local optima convergence. Utilizing stochastic attributes—such as generating a random parent solution population—improves the GA's performance. In the implemented algorithm, several tunable parameters exist - elitism, crossover, and mutation. An individual parent represents a unique array solution. Fig. 2 shows how the arrays are represented as strings for the GA.

Each cell of an individual parent string correlates to a section of the ocean and includes either a one, indicating a WEC's existence in that ocean section; or a zero, indicating the lack of a WEC's existence in that ocean section. The binary GA readily evaluates the minimum separation distance between devices – a previously unexplored aspect of array design. The effects of the minimum separation distance are shown in section 7.1.

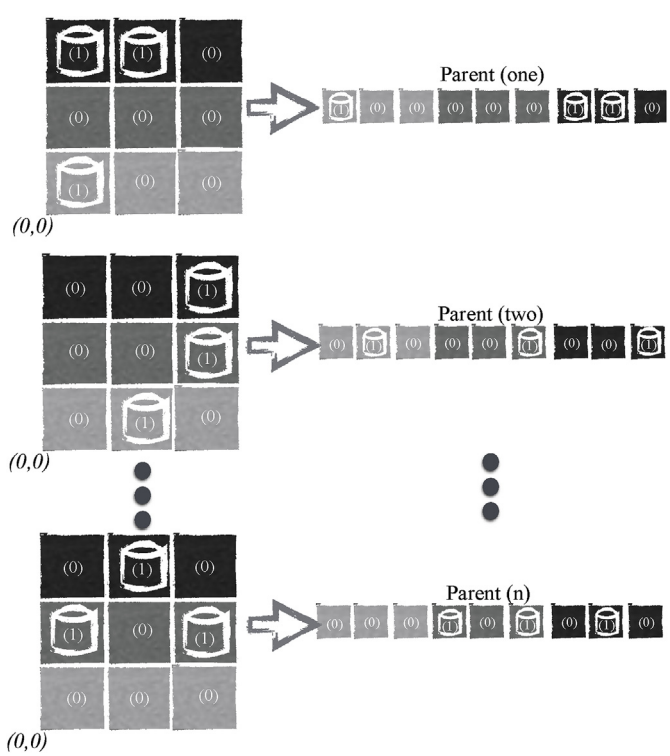

Fig. 2. Example of the relationship between physical arrays and parent strings.

Once generated, the random initial parents are evaluated and ranked by objective function (Eq. (1)). The elitism function clones an upper percentage of the sorted parent population by copying potential solutions directly to the children set. To balance this elitism, the same percentage of lowest-ranked solutions are removed from the parent set. After elitism, pairs of solutions in the parent population are mated via crossover. Because the WECs are located sparsely throughout the space and the number of devices is constrained to a set value, multi-point crossover is intractable. Instead, our integrated method creates the crossed-over children population by placing WECs in locations extracted from pairs of parent population solutions. This method of crossover ensures that the number of WECs within each new layout remains constant by equally exchanging devices between two solutions to create two new unique solutions. Specifically, children solutions are created in pairs by randomly selecting device locations from two parent solutions and combining them in a manner that creates two new solutions which have devices in locations that are extracted from each parent. Essentially, if a new child solution is examined, it will have device(s) that are in the exact position(s) as one of the parents and device(s) that are in the exact position(s) as the other parent. No child solution's device location will be entirely unique when comparing against the parents'; however, the child solution as a whole will be unique (assuming the two parent solutions weren't identical to begin with). Fig. 3 demonstrates the implemented crossover method. The selection of WEC locations to swap is tunable (selecting the number of WEC locations to swap) and random (selecting which locations will be swapped).

Crossover is performed on a defined upper percentage of the parent population including the parent solutions used for elitism. With crossover complete, mutation is performed on the resulting children. For mutation, randomly selected devices in a small percentage of randomly selected solutions receive new locations. This is achieved by first randomly selecting a cell from a randomly selected solution and changing the contained value. Since we are operating with a binary convention, the cell contains either a 1 (indicating a WEC) or a 0 (indicating the absence of a WEC). Depending on the selected cell's value (either a 0 or a 1) a cell in the same solution but with the opposite value is also randomly selected and its value changed to maintain the required number of devices within the solution. After elitism, crossover and mutation, and only if necessary, the children population is filled with randomly generated layouts so that the same number of solutions as the parent population is attained. The children population solutions are then evaluated using the objective function shown in Eq. (1) and ranked according to this objective function evaluation.

After ranking, the population is evaluated for convergence. Elitism ensures that the solution with the best objective function is maintained

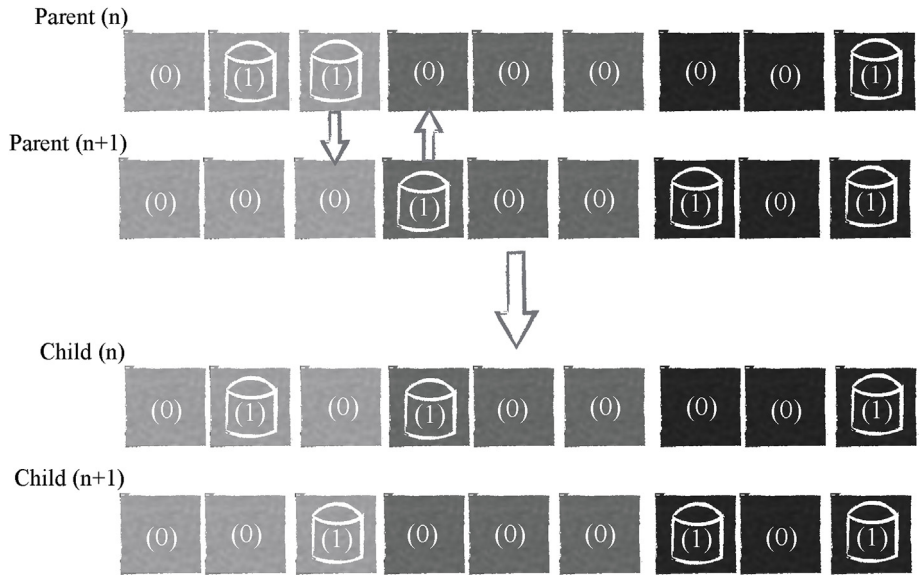

Fig. 3. Illustration of the crossover method used in this work.

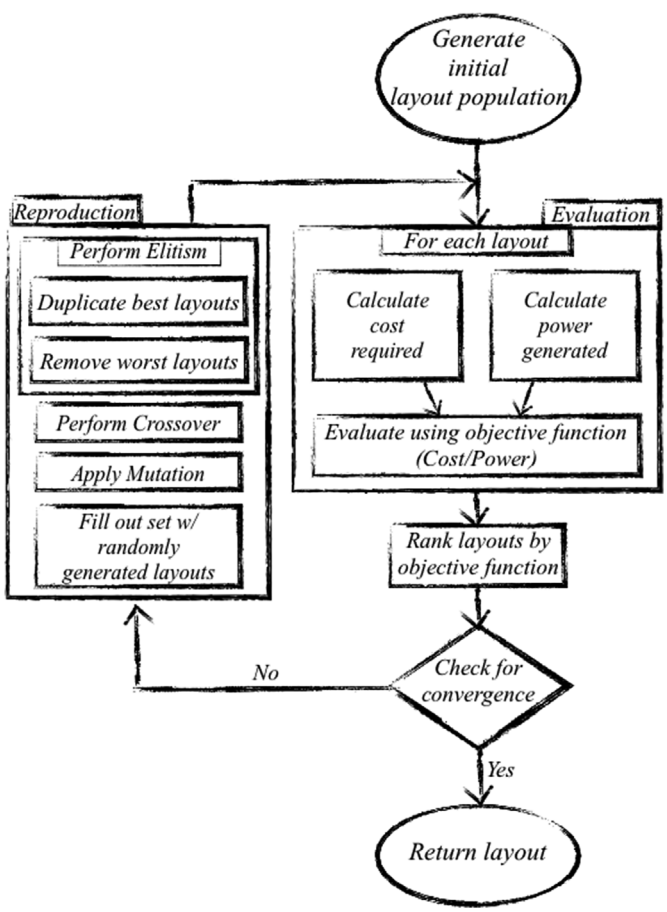

Fig. 4. Flowchart depicting Genetic Algorithm approach.

or updated between populations. Consequently, convergence is defined as a percentage of the population having an identical layout and objective function to the best solution. Once convergence is attained the algorithm returns the converged solution as the reported optimal array layout. If convergence is not attained the children population becomes the next parent population and the process continues. Fig. 4 shows the pseudocode for the GA used in our work.

4. Modeling

There are two models used for the objective function in this research: one for the development of array power, and one for array economics. Computational models calculate and predict the necessary factors of array layouts and the accuracy of the optimization method depends on the accuracy of the models utilized.

4.1. Power model

In previous research, power has been the driving consideration for determining optimal device arrangements. This emphasis is due to the vast availability of the wave energy resource and the potential ability of WEC arrays producing more power than the same number of devices in isolation. Specifically, work in array design has focused on maximizing the interaction factor, q. Eq. (2) defines q as (DeAndrés et al., 2014):

$$q = \frac{P_{array}}{N.P_{isolated}} \tag{2}$$

P_{array} represents the total power produced by an array of devices, $P_{isolated}$ is the power of a single device acting in isolation, and N is the number of devices in the array. In scenarios where multiple WECs interact with the incident ocean waves, the value of q has been theoretically found to be greater than one (Borgarino et al., 2011). Such a value of q indicates that devices could positively impact array power development when placed in specific layouts.

When an incident wave encounters a floating body (in this case, a WEC) two behaviors affect the value of q. First, the object begins to bob and waves radiate away from the body – like the ripples from a stone thrown into a pond. Second, the incident waves pile up and "bend" around the device. Consequently, the wave height increases. If devices are placed to benefit from these radiated and diffracted waves, the device can generate more power than it would in isolation (McNatt et al., 2014).

Existing software approaches, such as the linear wave-body software WAMIT (2012), can be used to calculate the power produced by an array of devices in a given sea state, but this software is prohibitively computationally expensive for use within an iterative optimization method. Alternatively, McNatt et al. has created a novel method for calculating power produced by an array of WECs that utilizes WAMIT once, for a given device geometry, and then analytically calculates the power produced for different array configurations (McNatt et al., 2014).

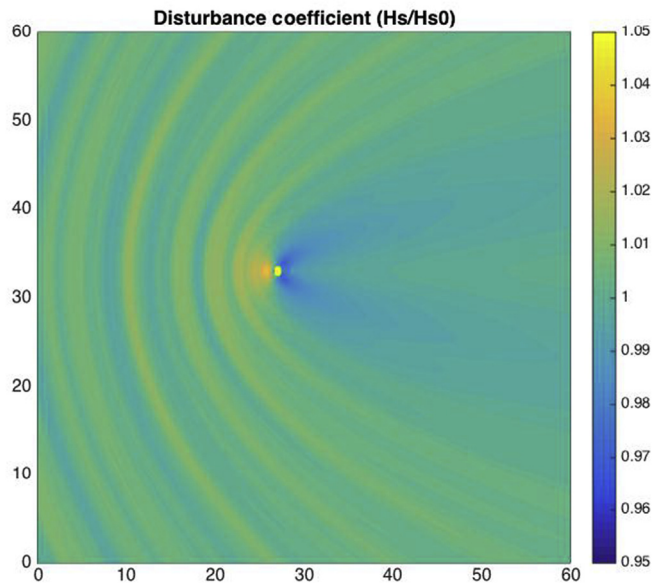

Fig. 5. Change in wave height (m/m) caused by an isolated device (The X- and Y-axes units are meters).

The damping, added mass, and hydrostatic matrices of a WEC in isolation are determined using WAMIT. These hydrodynamic properties are found for a specific device geometry and water depth, as well as for a range of wave periods and directions. Fig. 5 shows the behavior of a single device in a wave field.

Using the hydrodynamic properties of a single device generated in WAMIT, the analytical model described in (McNatt et al., 2014) extrapolates these effects to multiple devices in an array. Accounting for the orientation of each device, the complex excitation force and damping of the entire array is found using the scattered waves of a plane incident wave and the radiated wave coefficients (McNatt et al., 2014). With this information, the power developed by an array is found using Eq. (3) (Cruz, 2008).

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

In Eq. (3), $\mathbb{X}$ is the complex excitation force and $\boldsymbol{B}$ is the damping of the array. For this work, the damping of the power take-off is fixed for all devices in the array.

4.2. Cost model

The cost associated with developing, deploying, and maintaining a WEC array should be included in an algorithm's objective function, but has been previously neglected in WEC array optimization work. Considering only an array's power development as a system objective lacks the realism necessary for wave energy industry's success. The cost model used in our optimization work comes from Sandia National Lab's (SNL's) Reference Model Project (RMP) (Previsic, 2012). While not a calculating tool specifically, this reference model includes subsets of costs for different WEC array nameplate capacities. There are many assumptions involved, but these are explicitly stated within the RMP, and the RMP can be readily updated as new information becomes available. Figs. 6 and 7 show examples of information provided by the RMP.

For our developed optimization method, the cost equation was formulated by fitting a polynomial to the information provided by SNL's RMP and is shown in Eq. (4). The values of the RMP are based on reference model 3, which is a variation of a heaving point absorber (Previsic, 2012).

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

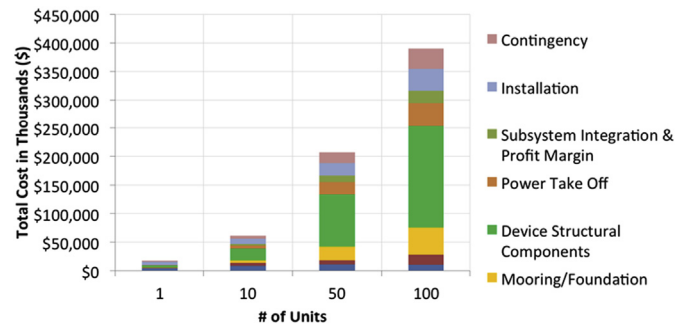

Fig. 6. Capital costs for four different sized arrays from SNL'S RMP (Previsic, 2012).

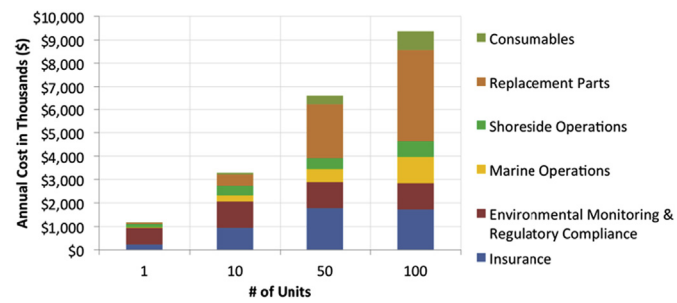

Fig. 7. O&M costs for four different sized arrays from SNL'S RMP (Previsic, 2012).

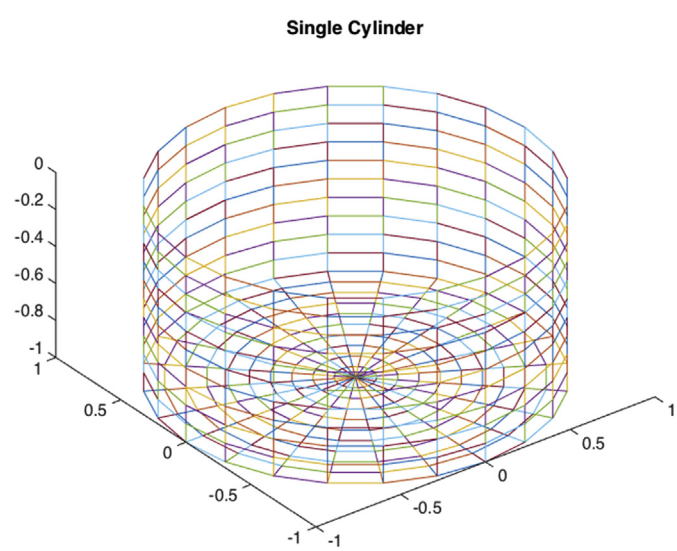

Fig. 8. Truncated cylinder utilized in optimization methods. (The X-, Y-, and Z-axes units are meters).

In Eq. (4), the cost (in USD) of an array is based solely on N, the number of devices in an array. This formulation serves as a placeholder which we will update with new information as it is developed (Sharp and DuPont, 2015a). Due to the offshore renewable energy sector being in its early stages, the economics involved are often unknown or are intellectual property. We understand that Eq. (4) is limited and recognize that the economics of arrays will greatly, if not primarily, influence future development of WEC array design. It is therefore important to include whatever knowledge is currently available regarding the economics of an array (Sharp and DuPont, 2015c).

5. Problem formulation

To achieve our preliminary results, five scaled, truncated cylinders

Table 1
GA tunable parameters.

Parameters				
	Case 1	Case 2	Case 3	Case 4
Minimum Separation Distance	3 m	4 m	5 m	6 m
# Of Parents	100	100	100	100
Elitism Rate	10%	8%	8%	8%
Crossover Rate	80%	84%	84%	84%
Mutation Rate	0.2%	0.2%	0.2%	0.2%
Convergence Requirement	50%	50%	50%	50%

are placed in a Bretschneider spectrum of unidirectional waves. The heave-constrained cylinders represent point absorber type WECs acting in the vertical direction, and the unidirectional waves indicate that the incident waves come from a single cardinal direction. Placed in a water depth of 8 m, the cylinders have a diameter of 2 m and a draft of 1 m as shown in Fig. 8. We used a scaled system, with the same device geometry, sea state, and water depth as (Child and Venugopal, 2010), to better compare against Child and Venugopal's previous work. The incorporated Bretschneider spectrum had a modal frequency of 0.2 Hz, a significant wave height of 2 m, and periods ranging from 4 s to 8 s. Again, these parameters were chosen based on the work of Child and Venugopal (2010), to facilitate comparison.

The parameters used to achieve the preliminary results are shown in Table 1. Since information on the minimum distance between devices is unknown, this minimum separation distance is deliberately varied for each case. The chosen values indicate the scaled nature of our problem formulation.

WECs are placed in a 10 × 10 grid that has 100 different potential WEC locations, resulting in over 9 (10^9) total potential layouts. The population size was chosen to balance computational efficiency and potential-solution diversity. Since a GA is a population-based optimization method that doesn't guarantee global optimality, we keep the algorithm from converging too quickly by having a large enough population. However, we also The unidirectional wave field and single degree-of-freedom WEC implementation serve as a test case for proving the efficacy of our GA method. As we adjust the minimum spacing requirement, the size of the represented physical space changes accordingly – the smallest being 30 m by 30 m (Case 1) and the largest being 60 m by 60 m (Case 4).

6. Results

Fig. 9–12 show the suggested arrays developed from the four test cases listed in Table 1. For each test case, we ran the algorithm ten times. The results shown are those with the best overall objective function evaluation for each test case and also appeared consistently throughout each individual case. For all the test cases, waves are unidirectional – coming from the west or directly from the left in Figs. 9–12.

For each of the results presented, the interaction factor, q, is calculated as described in Eq. (2) and the values are shown in Table 2.

7. Discussion

Utilizing a scaled test case scenario, our binary genetic algorithm determined optimal layouts for four different allowable minimum separation distances. When designed in an informed way, the layout of WEC devices in an array scenario can increase power production through device interaction as well as potentially minimize the involved cost through shared infrastructure. Prior to our work, WEC array design research considered maximizing an array's power production with little understanding of the influence of device spacing on said power production. As a note, the results shown in Figs. 9–12 were found by running the algorithm ten times per case. The results shown are not only the best found from these runs, but were also found repeatedly. Additionally, every start of the algorithm begins with a unique set of random initial parents to minimize the possibility of population takeover.

7.1. Spacing effect

When considering the deployment of devices in real sea scenarios, we must allow for a watch circle around individual devices to prohibit or minimize physical contact with other devices and entanglement of mooring systms. Examining the depicted arrays in Figs. 9–12, varying shapes are observed depending on the minimum allowable distance between WECs. In Case 1, when restricted to a 3-m minimum separation distance, the devices line up in pairs – parallel to the oncoming wave. However, when the minimum distance increases to 6 m, the converged layouts place themselves in a diamond shape with one corner pointing towards the oncoming incident wave. This transition is due to the dissipation of radiated waves. As discussed in section 4.1, a device can alter the wave field and power experienced by its neighbors through its radiated and diffracted waves.

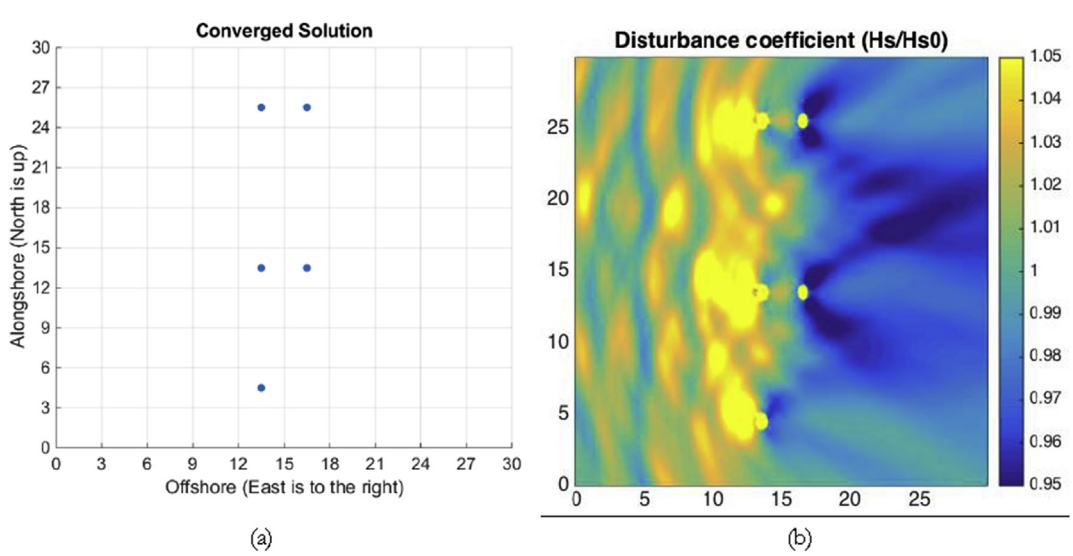

Fig. 9. (a) Layout from case 1 with 3-meter minimum separation distance and (b) The layout's corresponding wave field (The X- and Y-axes units are meters).

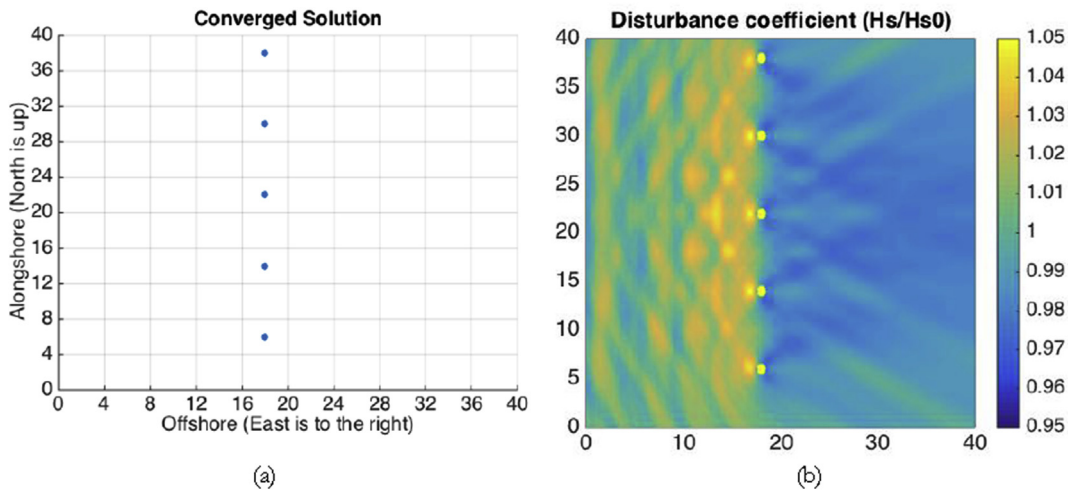

Fig. 10. (a) Layout from case 2 with 4-meter minimum separation distance and (b) The layout's corresponding wave field (The X- and Y-AXES units are meters).

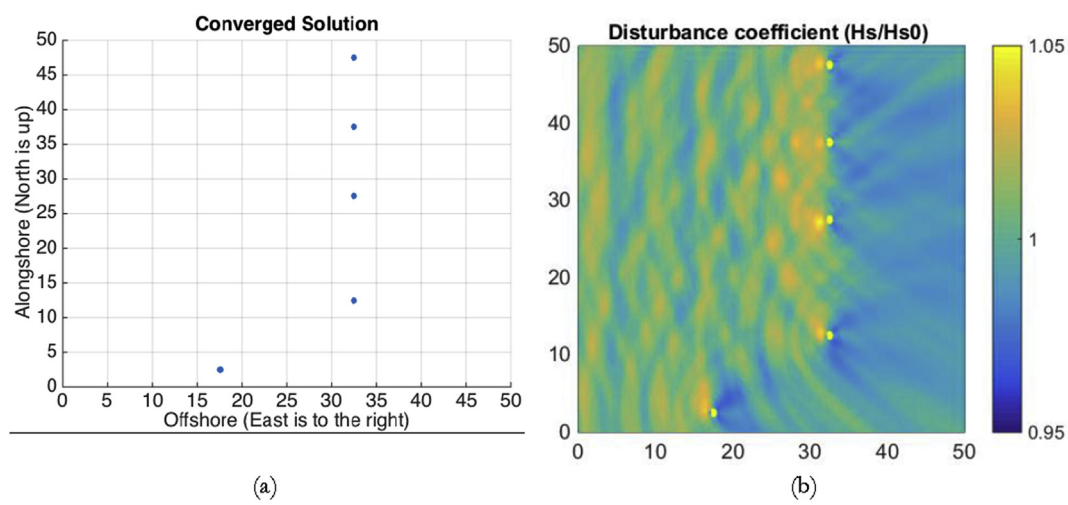

Fig. 11. (a) Layout from case 3 with 5-meter minimum separation distance and (b) The layout's corresponding wave field (The X- and Y-axes units are meters).

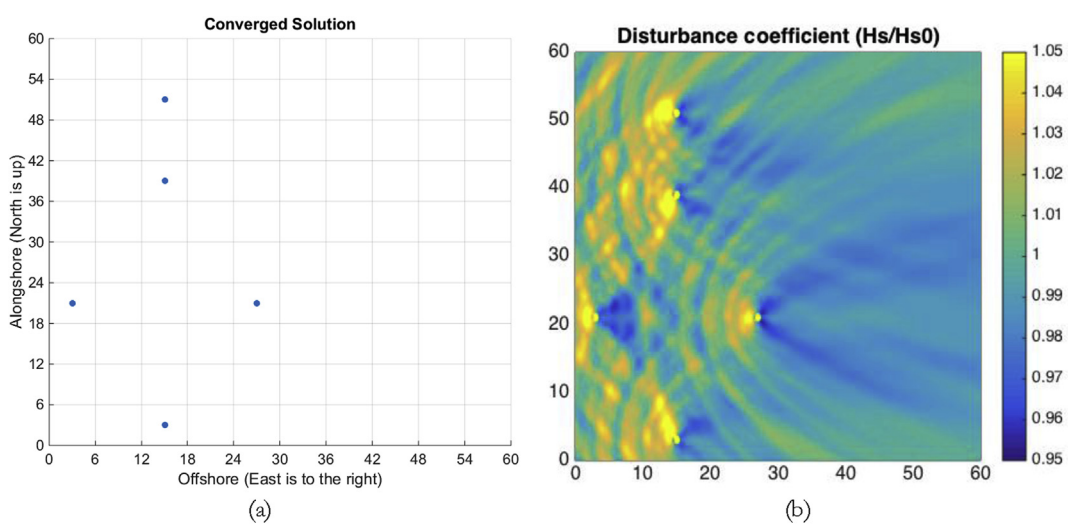

Fig. 12. (a) Layout from case 4 with 6-meter minimum separation distance and (b) The layout's corresponding wave field (The X- and Y-axes units are meters).

For the 3-m separation distance shown in Fig. 9, the devices appear to be utilizing the radiated waves of their immediate up-wave neighbors. However, with increased separation distance, the WECs place themselves to benefit from their neighbor's diffracted waves. As indicated by the interaction factors reported in Table 2, the overall optimal layout occurs when devices capitalize on upstream radiated waves. An increase in allowable minimum separation distance initially generates layouts with worse q values until the diffracted waves can be

Table 2
Calculated interaction factor for each test case.

	Case 1	Case 2	Case 3	Case 4
q	1.024	1.021	1.016	1.019

Table 3
Interaction factor comparison between presented result and previous research results.

	Method		
	Presented Genetic Algorithm	Child & Venugopal (Child and Venugopal, 2010)	
		Parabolic Intersection	MATLAB'S Genetic Algorithm
Interaction Factor (q)	1.019	0.9961	0.9942

effectively captured. At which point, the interaction factor increases again. It is important to note that if different parameters are used in the applied Bretschneider spectrum, resulting layouts would differ from these shown (Borgarino et al., 2011). Also, the difference in layout configurations based on the minimum separation distance is likely directly related to the sea state that the initial individual WEC experiences.

If we consider what might happen at a large scale.

7.2. Comparison to results of previous research

Our results validate the ability of our created optimization method to find array arrangements that maximize power produced. As was presented in Section 2, Child and Venugopal utilized two methods for optimizing a layout, as shown in Fig. 1 (Child and Venugopal, 2010). Table 3 shows the comparison of the objective function evaluation of Case 4 to those layouts shown in Fig. 1. Case 4 was chosen for comparison due to a similar minimum separation distance (6 m) between devices, as seen in (Child and Venugopal, 2010). To ensure a more equivalent comparison, we calculated the interaction factors of all three layouts using our presented power model.

When comparing the interaction factors from Table 3, the WEC arrangement found by our method achieves a higher interaction factor than the example layouts from Child & Venugopal. It should be noted that the interaction factor found for the results of Child & Venugopal when using the method presented in this article differ from their reported interaction factors – 0.9961 versus 1.787 for the Parabolic Intersection (PI) method and 0.9942 versus 2.1010 for the MATLAB GA method (Child and Venugopal, 2010). This indicates that the power is being calculated in a different manner than what we have presented. Additionally, the referenced results from the parabolic intersection and MATLAB GA methods use a regular wave set rather than the Bretschneider spectrum utilized by our presented optimization method. These differing wave fields would also affect the power developed. We chose to utilize the Bretschneider spectrum for this comparison to include some realistic complexity.

8. Conclusion

In WEC array development, the optimal layout for devices is determined to be dependent on the local sea state, device design and geometry, the minimum distance between devices, and costs based on local information. Additionally, for array optimization work to remove industry implementation barriers, all factors that impact the WEC array system should be accurately modeled. Currently, power is the driving factor regarding array configurations. We have shown our optimization method to be useful for generating theoretical WEC arrays that maximize power by achieving interaction factors greater than one. Our preliminary GA results show the capability of this method to aid the industry in better understanding optimal arrangement.

Offshore renewable energy industries are in relatively early stages of research and development. As such, the economic factors, and their corresponding influence, are not well known. Yet, cost will likely be a driving factor of grid-connected layout design. As such, it is vital to prepare for the inclusion of up-to-date cost models when they become available. Eq. (4) represents an introductory cost model (that is consistent to similar research) that can be easily updated. This work demonstrates the effect that radiated and diffracted waves can have on an array's optimal layout if, for instance, a minimum spacing requirement is implemented to minimize harmful physical interaction or to allow for easier operations and maintenance. Comparing against previous work shows that using our genetic algorithm approach created specifically for WEC array optimization will provide results with improved interaction factors. Using an objective function similar to previous research, but with the inclusion of cost, future work will involve removing simplifications such as discretized space, wave direction, and fixed number of devices. Also, as cost and power models are improved, and environmental impact models created, we will update the algorithm accordingly.

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