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Multi-Objective Shape Optimization of Multi-Axis Wave Energy Converter

A. Shadmani[1,2] , M.R. Nikoo[3] and A.H. Gandomi[4,5]

**[1]Department of Maritime Engineering,
Amirkabir University of Technology, Iran
[2]Department of Electromechanical, Systems, and Metal Engineering,
Ghent University, Belgium
[3]College of Engineering, Department of Civil and Architectural
Engineering, Sultan Qaboos University, Oman
[4]Faculty of Engineering and Information Technology,
University of Technology Sydney, Ultimo, Australia
[5]University Research and Innovation Center (EKIK),
Óbuda University, Budapest, Hungary**

Abstract

Wave power is amongst the most promising forms of renewable energy, with a potential of 337 GW globally, compared to other renewable sources such as wind and solar; however, wave energy technologies are not completely. This necessitates the optimal design of wave energy converters (WECs) to commercialize these technologies. To this end, several optimization techniques have recently been developed, which the effectiveness of the state-of-the-art evolutionary algorithms has not been compared or contrasted for WECs. A new and innovative WEC type with respect to two body point absorbers with multi-axis motion, i.e., surge, heave, and pitch, has been considered with respect to different geometry. This paper presents a framework for the shape design of WECs utilizing multi-objective particle swarm optimization (MOPSO) in response to two main objective functions, i.e., maximization of power output and minimization of construction cost. Finally, the

results demonstrated that the optimal shape design of multi-axis WEC in terms of maximum power output and minimum construction cost is octagonal shape, compared to cylindrical and triangular shapes.

Keywords: wave energy, wave energy converter, shape design, multi-objective optimization, particle swarm optimization

1 Introduction

High energy potential is found in ocean waves. For this reason, many different types of wave energy converters (WECs) have been developed to design devices with reduced costs and increased annual energy production (AEP). Design optimization offers the opportunity to explore more of the design space while avoiding expensive build and test iterations and it has been used to improve energy efficiency of a range of commercially developed systems. For instance, it has been applied to improve efficiency of buildings [1], hybrid solar-wind generation plants [2], also in combination with storage technologies [3], or combined cooling, heating, and power (CCHP) systems [4]. This type of design optimization is particularly relevant for emerging technologies such as wave energy converters, where improved early-stage designs significantly impact technology advancement towards commercialization.

Previous studies show that one of the largest cost reduction potentials is associated with the WEC structure, i.e., hull [5], [6]. Apart from the high capital expenditure associated with the device hull, the geometry of the hull is crucial for the device hydrodynamic, and, thus, for the AEP. The cost reduction potential and key hydrodynamic characteristics associated with the device hull have resulted in several device hull geometry optimization studies, which aim to maximise performance and minimise costs. A point absorber based on simple hull shapes using cylindrical geometries was studied by Gilloteaux et al. [7] to understand the effect of different control strategies on optimal device size.

All the above studies used geometry definitions based on simple shapes such as cylinders, barges, or ellipsoids. An approach capable of generating very diverse shapes was developed by McCabe et al. [8] using a more complex geometry definition based on B-spline surfaces. This initial method was applied to a surging and pitching device. This method was further developed and applied to a surging-only device in [9], where geometries were optimized using a single-objective genetic algorithm (GA). Shapes were optimized to maximize mean annual absorbed power and mean annual absorbed power in combination with the submerged volume.

There is a clear need for the development of a flexible and comprehensive method for hull geometry optimization due to the relevance of design optimization tools at early design stages, the high cost associated with the structure and the lack of general methodology and best practices for WEC geometry optimization. As previously identified by Weber et al. [10], this is key for the advancement of wave energy technologies. Such a method for hull geometry optimization represents a fundamental design aid for technology developers, but it can also serve to find bodies to assess different technologies, since it will build on a methodology for design comparison.

The present work addresses this gap by finding a suitable and efficient optimization method for WEC geometry optimization. With this purpose, the geometry definition is studied. Different geometry definitions are compared; cylindrical, triangular, and octagonal shapes. In addition, two main objective functions, namely maximum power output and minimum construction cost, are considered for a device oscillating in surge, heave, and pitch. A novel metaheuristic multi-objective optimization algorithm [11], [12], i.e., multi-objective particle swarm optimization (MOPSO), is applied to discover optimal shape design in terms of radius, height, and draught.

2 Methods

A multi-objective optimization problem with a number of competing objectives can be defined as follows:

$$Minimize: F(X) = f_1(X), f_2(X), \dots, f_G(X), \tag{1}$$

$$Subject\ to: R_i^{lower} \le x_i \le R_i^{upper}, i = 1, 2, \dots, d \tag{2}$$

where G is the number of objectives, d is the number of variables and $[R_i^{lower}, R_i^{upper}]$ are the boundaries of the i-th variables. In Pareto dominance, given that there are two candidate solutions: $Y = (y_1, y_2, \dots, y_d)$ and $Z = (z_1, z_2, \dots, z_d)$, vector Y dominates vector Z (denoted as $Y \succ Z$) if and only if, the objective function value of vector Z in all the G objective space, and the objective function value of vector Y is less than to the objective function value of vector Z in at least one of the G objective space, as formulated in Eqs. (3) and (4).

$$f_g(Y) \le f_g(Z), \forall g \in \{1, \dots, G\} \tag{3}$$

$$f_g(Y) < f_g(Z), \forall g \exists \{1, \dots, G\} \tag{4}$$

Solution Y is considered a non-dominated Pareto optimal solution if other solutions do not dominate it. No better solutions than Y exist in the particular problem. However, similarly good solutions may exist, dependent on user perception. A solution Y, which is an element of X, ($Y \in X$) is called Pareto-optimal if and only if, there does not exist a solution Z, which is an element of X, that dominates any solution Y, as formulated in Eq. (5).

$$\nexists Z \in X | f(Z) \succ f(Y)| \tag{5}$$

The Pareto optimal set is defined by a set of solutions that fulfill Eqs. (3) and (4), while at the same Eq. (5) holds true. The collective fitness values obtained from these solutions are known as the Pareto-front or trade-off surface.

In 1995, Kennedy and Eberhart developed Particle swarm optimization (PSO) [13], an algorithm inspired by swarm behaviour exhibited in fish and bird schooling. To this end, one of the earlier attempts to solve multi-objective problems using PSO was made by Coello and Pulido [14] using multi-objective Particle swarm optimization (MOPSO). The algorithm uses the concept of Pareto dominance to find solutions for multi-objective problems. It also employs a secondary population or external archive to store non-dominated solutions and guides the search of future generations. A special mutation operator is also implemented to improve the search procedure. The MOPSO algorithm is presented in Figure 1.

1	Initialize the population, X^j for $j = 1, 2, \ldots, n$; where n is the number of population.
2	Initialize the speed, VEL^j for each particle as follow: $VEL^j = 0$
3	Evaluate each particle
4	Store non-dominated solutions in archive/repository, *REP*.
5	Generate hypercubes
6	Initialize the memory of each particle by storing initial X^j positions as best found positions so far, BFP^j as follows: $BFP^j = X^j$
7	Compute the speed of each particle as follow: $VEL^j = W \times VEL^j + R_1 \times (BFP^j - X^j) + R_2 \times (REP - X^j)$ where W (inertia weight) takes a value of 0.4; R_1 and R_2 are random numbers in the range of [0…1]
8	Compute the new positions of each particle as follow: $X^j = X^j + VEL^j$
9	Maintain the particles within the search boundaries
10	Evaluate each particle
11	Apply mutation to each particle
12	Update *REP* and hypercubes by inserting non-dominated solutions into the repository and eliminate dominated solutions from the repository.
13	Update each particle memory by replacing the previous best position with the current best position found by each particle
14	If maximum iteration is achieved, terminate. Otherwise, repeat step 7

Figure 1: MOPSO procedure.

MOPSO uses the Pareto ranking scheme to handle multi-objective optimization problems. The algorithm store previously generated non-dominated solutions by recording the history of the best solutions found by a particle.

Obviously, most of the designed two-body point absorber (2B-PA) WECs generate energy from a single mode of motion e.g., surge or heave. For this purpose, a design of multi-axis WEC could produce energy from multiple directions, like surge, heave, and pitch. In addition, different geometry of this 2B-PA was generated to compare its energy production and find optimal design. The initial design of multi-axis WEC is illustrated in Figure 2.

The hydrodynamic model is a critical part of any WEC design optimization process since it is one of the most important elements influencing the best WEC configuration. However, the hydrodynamic model used for WEC optimization forces is an uneasy trade-off between computing practicability and modeling accuracy [15]. The dynamics associated with point absorber WEC are presented as follows. A point absorber's dynamics are demonstrated using a floating cylinder. Newton's second law, stated in Eq. (6), describes the rules by which a body's motion must abide.

$$M\ddot{\xi}(t) = f_h(t) + f_g(t) + f_{pto}(t) + f_m(t) + f_{add}(t) \tag{6}$$

where WEC displacement is denoted by ξ; and $\boldsymbol{M}$ is the inertial matrix. The hydrodynamic, gravitational, PTO, and mooring line forces are denoted as f_h, f_g, f_{pto} and f_m, respectively. The term $\boldsymbol{f}_{add}$ is used to describe additional forces, such as those brought on by safety strategies. Each of these factors or quantities has a size relative to the quantity of WEC objects and degree of freedoms (DOFs) taken into account. There are six DOFs that a WEC body is capable of moving in: surge, sway, heave, roll, pitch, and yaw. Torque terms are used instead of the force vector components corresponding to the pitch, roll, and yaw motions [16]. Different components of the hydrodynamic force $\boldsymbol{f}_h$ are the Froud-Krylov (FK) force $\boldsymbol{f}_{FK}$, diffraction force $\boldsymbol{f}_d$, radiation $\boldsymbol{f}_r$, and hydrostatic force $\boldsymbol{f}_{hs}$, described in the following equations:

$$\boldsymbol{f_h} = \boldsymbol{f_{FK}} + \boldsymbol{f_d} + \boldsymbol{f_r} + \boldsymbol{f_{hs}} \tag{7}$$

$$\boldsymbol{f_{FK}} = \rho \iint_S \frac{\partial \phi_i}{\partial t} \boldsymbol{n}_h dS \tag{8}$$

$$\boldsymbol{f_d} = \rho \iint_S \frac{\partial \phi_d}{\partial t} \boldsymbol{n}_h dS \tag{9}$$

$$\boldsymbol{f_r} = \rho \iint_S \frac{\partial \phi_r}{\partial t} \boldsymbol{n}_h dS \tag{10}$$

$$\boldsymbol{f_{hs}} = \rho \iint_{\boldsymbol{S}} gz\, \boldsymbol{n}_h dS \tag{11}$$

It is important to remember that a WEC device is floating and motionless in the water; the excitation force is defined as $\boldsymbol{f}_e = \boldsymbol{f}_{FK} + \boldsymbol{f}_d$ and $\boldsymbol{f}_{hs} + \boldsymbol{f}_g = 0$. To calculate the excitation forces and hydrodynamic coefficients, a NEMOH BEM solver is used to describe the hydrodynamic behavior of the multi-axis WEC structure [17].

Several design factors or characteristics must be considered to determine the optimum geometry for any given WEC, including capturing the highest wave energy from certain frequency range, wave direction effectiveness, and reducing extreme dynamic motion. For this reason, the objective function of geometry optimization was considered as maximum power output and minimum construction cost, which certainly focused on minimizing the Levelized cost of energy (LCOE). A cylindrical, triangular, and octagonal geometry database has been created and employed in the MOPSO procedure. Additionally, the input of the optimization procedure was the wave energy spectrum based on the probability of occurrence of each sea state of a specified coastal region, which is depicted in Figure 3.

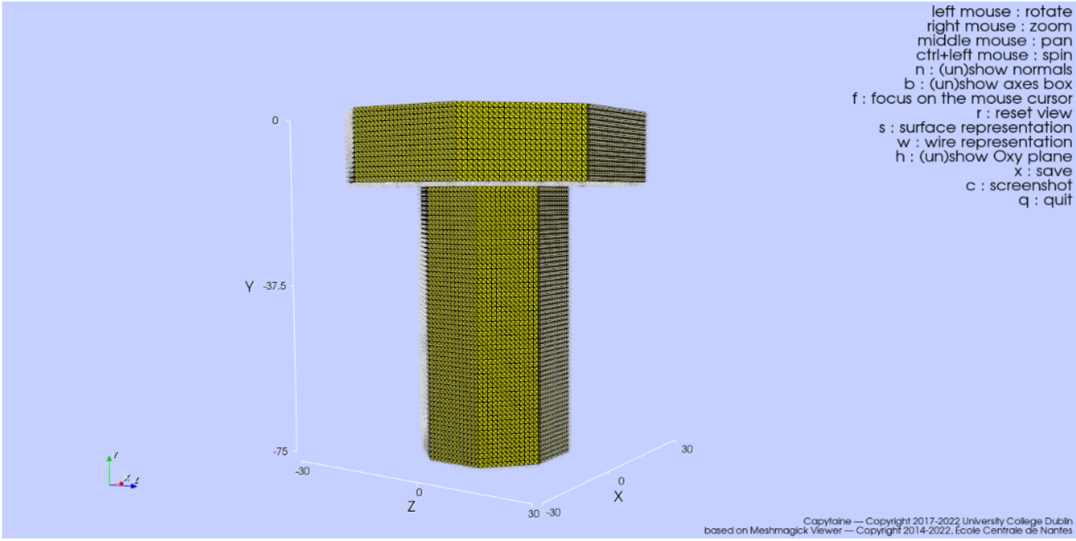


Figure 2. Design of multi-axis 2B-PA WEC

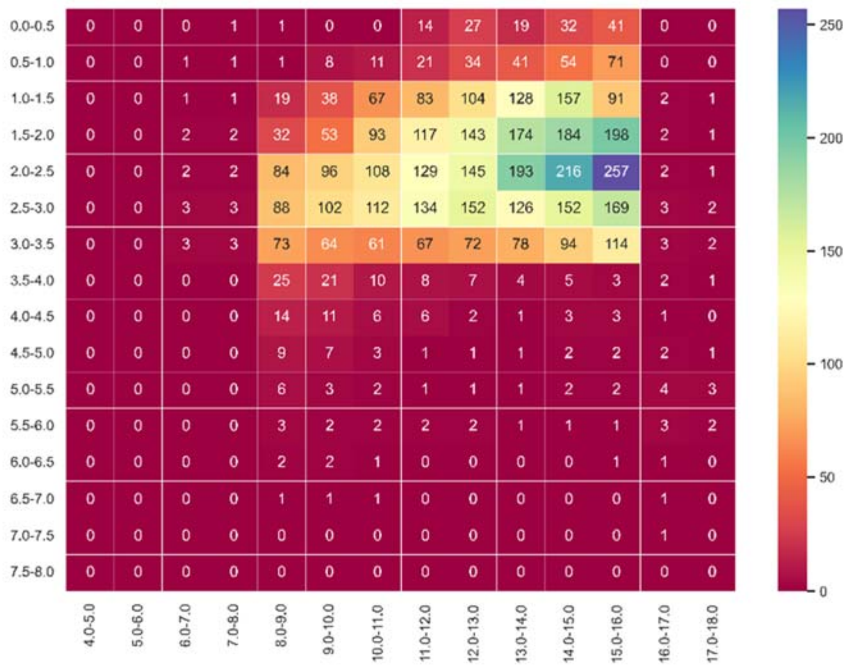
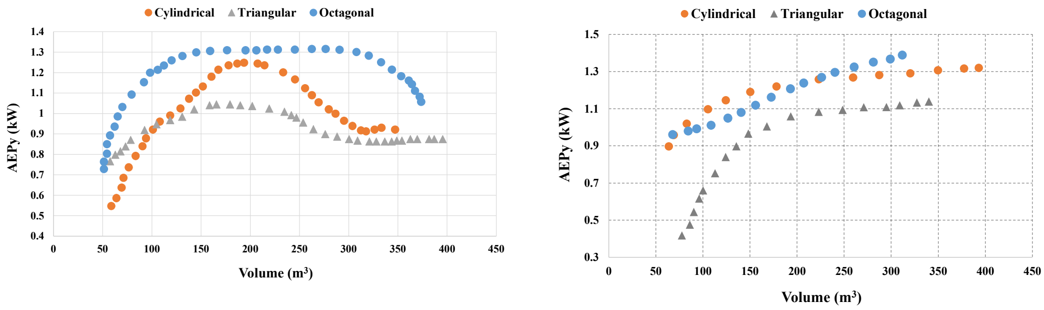


Figure 3. Probability of occurrence of sea state

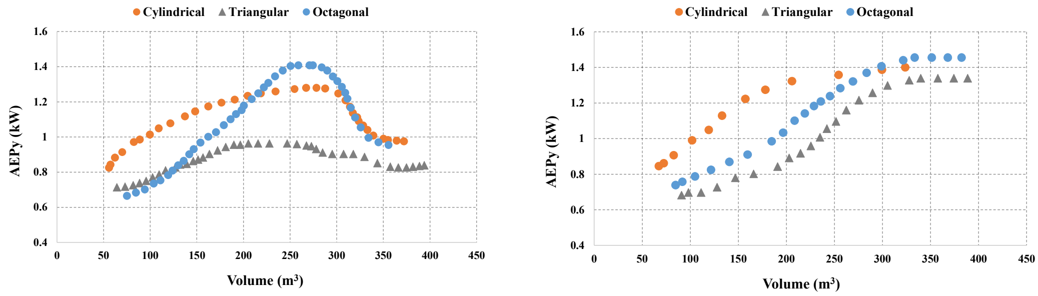
3 Results

This study presents multi-objective particle swarm optimization (MOPSO) to investigate the optimal design of a multi-axis two-body point absorber WEC. Different shape designs, namely, cylindrical, triangular, and octagonal have been considered in this study to compare each shape annual energy production (AEP) in terms of volume surface. The dimension of the radius varied between 1-35 m, and height and draught were in the range of 1-18 m.

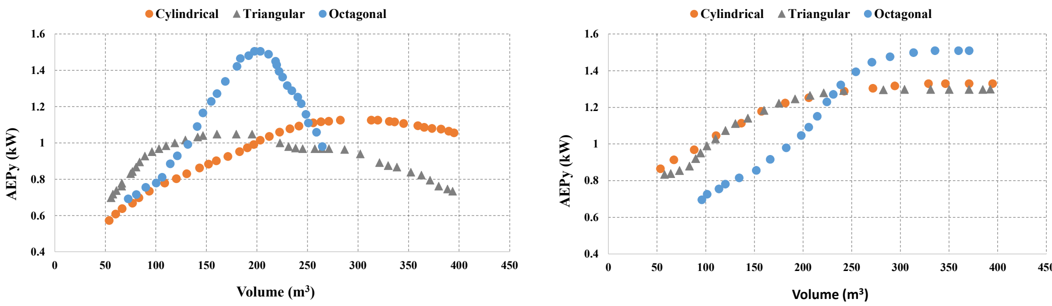
By solving the dynamic equation of the floating body, the structural response of the device was obtained, and the AEP and construction cost were calculated and compared.



(a) Radii variation



(b) Height variation



(c) Draught variation

Figure 4. AEP_y and Pareto front of cylindrical, triangular, and octagonal shapes

By comparing the results of each shape and size variation with respect to the MOPSO algorithm, it can be deduced that the octagonal shape with the derived values of 29, 13.6, and 16.3 m for radii, height, and draught are the optimal shapes and sizes for the multi-axis WEC to be deployed along a specified region. The results of the MOPSO algorithm for these three main dimensions against the volume of each shapes are shown in Figure 4. Changing the obtained WEC radius, height, and draught, the absorbed power and volume of the device varies between 1.13-1.22 kW and 168-262 m^3, 1.31-1.42 kW and 252-288 m^3, and 1.48-1.57 kW and 163-218 m^3, respectively, as can be seen in Figure 4. It also can be observed that the absorbed power and volume regarding the variation in the optimum dimension for octagonal shape is 1.32-1.39

kW and 150-300 m^3, 1.28-1.33 kW and 284-304 m^3, and 1.29-1.33 kW and 105-254 m^3, respectively. These results are not comparable to cylindrical and triangular geometries, with lower AEPys producing lower values, as is observable from the Pareto front results of each dimension variation in each shape. By examining the optimization figures, it is clear that many possible configurations are not optimal, demonstrating the importance of geometry optimization to the WEC's usability.

It can be seen in Figure 4 that increasing the dimensions resulted in more power to be extracted and decreased immersed volume. Comparing the results of these geometries with each other, it can be concluded that octagonal geometry is very effective for increasing the extracted power, which can be impressively enhanced by about 100 W.

Figure 5 depicts the LCOE outcome of the WECs regarding the construction cost, which the model was run for every sequence of converter power rating. Unfavorable results were achieved for a rated power of 20 kW, while the smallest LCOE was acquired for WECs valued at 100 kW. By examining the rated power, we can see that converters of 100 kW are best suited for the local wave environment, which this device produces the lowest energy costs. Comparatively, lower power ratings result in much less yearly energy output and higher energy costs.

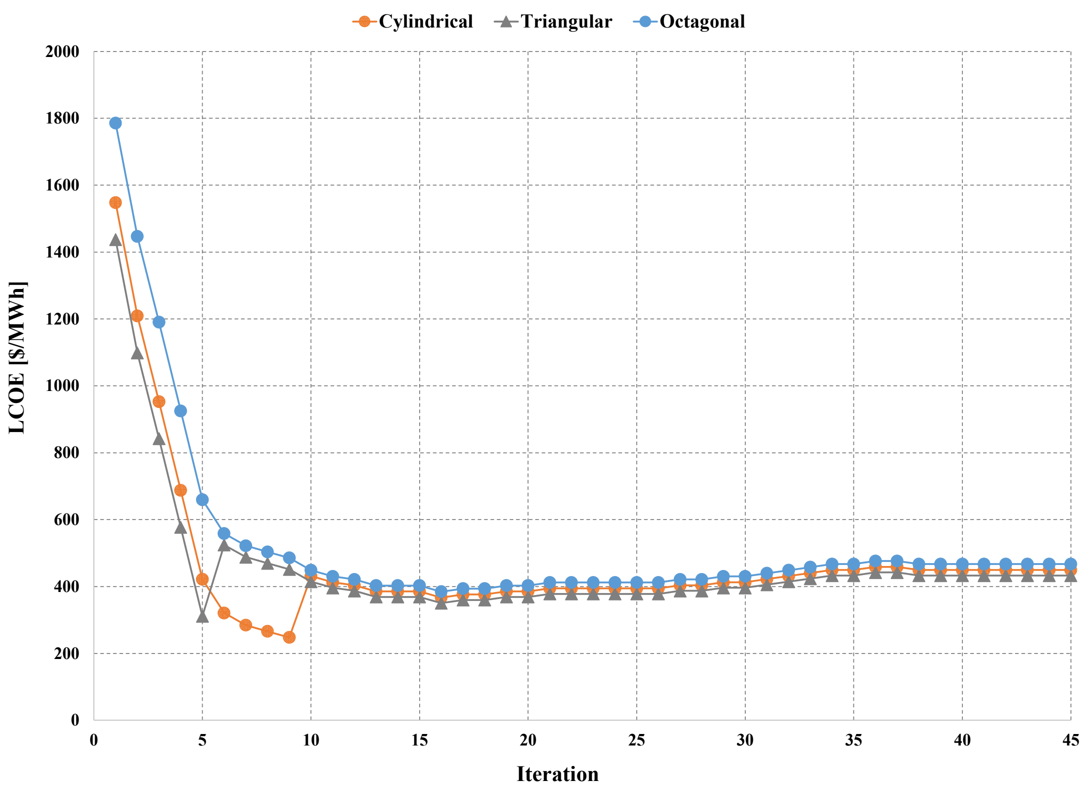


Figure 5. LCOE variation vs. iteration for cylindrical, triangular, and octagonal shapes

4 Conclusions and Contributions

This research proposes multi-objective particle swarm optimization (MOPSO) framework for optimizing shape design of a multi-axis WEC considering different geometries. A structure's optimal radius, height, and draught were calculated by simulating the system under no constraints, in which the hydrodynamic coefficient of each shape was calculated using NEMOH. Two main objective functions based on absorbed power and construction were developed in this study.

It has been shown that a novel model may be used to optimize wave power plants from a financial perspective, whereby minimizing the LCOE yields optimum solutions. The input used to determine the ideal geometry configuration was the annual wave energy spectrum. To this end, the optimal shape was the octagonal shape with radius of 29 m, height of 13.6 m, and draught of 16.3 m, respectively. The results of this show how sensitive the outcomes are to the many factors used in the compound hydrodynamical and economical design and wave power plant optimization.

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