Efficient wave energy converter optimisation via control co-design: A comparison of AI-based algorithms

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ABSTRACT: The transition to a sustainable, carbon-neutral global energy system requires a significant expansion of renewable energy sources. Among renewable energy technologies, offshore renewable energy (ORE) systems, including wave energy converters (WECs), offer promising alternatives to traditional fossil fuel-based energy generation. Lately, control co-design (CCD) techniques are becoming more popular to boost WECs commercial viability, but they present complex optimisation challenges due to the large amount of variables to be optimised. In this study, four global optimisation techniques—genetic algorithms (pattern search, particle swarm optimisation, and surrogate optimisation) are compared for WEC CCD applications. Through a case study of a two-degree-of-freedom cylindrical WEC, the convergence speed, robustness, and effectiveness of each technique in finding optimal solutions for WEC design and control are assessed. Results demonstrate that all four optimisation techniques converge to similar results, in a fraction of the time required by brute-force methods. Moreover, trajectory-based optimisation strategies, such as pattern search and surrogate optimisation, show promise for efficiently navigating the solution space and avoiding local minima.

1 INTRODUCTION

Towards a sustainable, carbon-neutral energy system, the expansion of renewable energy sources is crucial to shift away from the reliance on fossil fuels. This transition is aligned with the goals outlined in the Paris Agreement (United Nations 2015) and underscored by the latest assessment from the Intergovernmental Panel on Climate Change (IPCC) (IPCC 2023), which aims to address the urgent need to mitigate the most adverse effects of climate change (IPCC 2018). While wind and solar energy technologies have reached maturity and reliability, achieving the necessary scale-up to accelerate this transition effectively will require support from additional and diverse energy sources. For instance, the International Renewable Energy Agency (IRENA) projects a staggering 14 TW increase in global renewable energy installed capacity requirement by 2050 (IRENA 2019), highlighting the immense challenge ahead. However, given the magnitude of the challenge, other less conventional renewable energy sources will also be necessary for an effective and quick transition. In this context, untapped offshore renewable energy technologies, including wave and tidal energy, emerge as a promising alternative.

While the potential of ocean waves for energy generation is immense, wave energy technologies are not yet ready for commercialisation. Currently, all existing projects (totalling about 2.5 MW of installed capacity worldwide) are focused on research and demonstration (Guo & Ringwood 2021). At its current stage of development, wave power is anticipated to play a distinct role in the energy mix, such as providing energy to isolated islands (Wang et al. 2023) or offering a more reliable, less variable and more predictable energy source (Fusco, Nolan, & Ringwood 2010, Astariz & Iglesias 2016, Sasaki 2017). However, the hydrodynamic performance of wave energy converters (WECs) is often optimised either under uncontrolled conditions (Babarit 2010) or passive control conditions (De Andrés et al. 2014, Bozzi et al. 2017, Penalba et al. 2017), resulting in WECs designed for underexcited behaviour. However, it is crucial to operate WECs considering optimal control strategies that maximise energy extraction in order to render wave energy economically viable (Ringwood et al. 2014). The disparity between the behaviour of the optimised WEC design and its behaviour when advanced control strategies are applied is addressed by imposing design constraints on the controller, which may lead to suboptimal outcomes (Mérigaud & Ringwood 2018).

To tackle this challenge, the control co-design (CCD) approach, where energy-maximising control strategies are integrated into the optimisation process from the early stages, has recently gained traction for WECs as a more holistic approach. In essence, this design paradigm underscores a control-informed optimisation approach. Numerous studies in the literature have illustrated the advantages of CCD in optimising various parameters related to WECs. For instance, (Coe et al. 2020) emphasise that CCD strategies play a significant role in achieving an optimal structural design for the absorber geometry, aligning it with the energy-maximising control scheme (Rosati & Ringwood 2023). However, the computational complexity of CCD problems increases exponentially with the number of variables to be optimised. As a result, most of the studies currently published only consider one or two variables.

In essence, CCD approaches combine two optimisation loops: there is an inner optimisation loop for the controller trying to maximise energy extraction, while another external optimisation loop optimises the geometric parameters of the WECs trying, for example, to reduce the converted energy cost. In such an external loop, in particular, it is becoming more common to apply AI-based optimisation algorithms (such as machine learning or genetic algorithms) (Zarketa-Astigarraga et al. 2023, Coe et al. 2020). However, in most cases, they are employed to optimise WEC geometry without considering an optimal control strategy, which is then applied to the final geometry.

The present study seeks to conduct a critical comparison of some of the most commonly employed AI-based optimisation algorithms in the literature. The objective is to determine whether any of these strategies offer advantages when applied to the CCD of WECs. To accomplish this, a case study involving a multi-degree-of-freedom (DoF) cylindrical WEC is investigated, with the optimisation focusing on both its height and diameter.

The remainder of the paper is organised as follows: Section 2 introduces the control co-design methodology proposed in this study, and Section 3 the global optimisation algorithms used to solve such CCD problem. Then, the application case study is introduced in Section 4, and the results obtained for the four optimisation algorithms are shown in Section 5. Finally, some conclusions are drawn in Section 6.

2 CONTROL CO-DESIGN METHODOLOGY

This section introduces the CCD methodology considered in this study. Section 2.1 provides the mathematical model describing the WEC while, Section 2.2 explains how the CCD methodology is defined.

2.1 *WEC modelling*

This study focuses on a two DoF submerged point absorber (PA) WEC system, considering surge and heave motions, inspired by the CETO WEC developed by Carnegie (Rafiee & Fiévez 2015). In the context of wave energy conversion, the WEC movement relative to the seabed is induced by incoming waves, and this motion is then converted into electricity via a power take-off (PTO) system. To regulate the WEC motion, a control force can be exerted through the PTO system. In this investigation, the PTO system is anchored to the seabed and comprises three separate linear generators, offering the ability to control the various DoFs independently.

The WEC system under consideration is referenced at its equilibrium position in an undisturbed wave field. Following standard linear potential flow assumptions, the motion of a multiple DoF WEC can be described using Cummins' equation (Cummins 1962) for $t \in \mathbb{R}^+$ as,

$$M\ddot{z}(t) + f_r(t) + f_{\mathrm{h}}(t) = f_{\mathrm{ex}}(t) - f_{\mathrm{PTO}}(t), \tag{1}$$

where $z(t)$ represents the displacement of the WEC in surge and heave and, consequently, $\dot{z}(t)$ and $\ddot{z}(t)$

its velocity, and acceleration, respectively. Furthermore, in Equation (1), $f_{\mathrm{ex}}(t)$ and f_{PTO} denote the wave excitation force and control force applied through the PTO system, respectively, $f_{\mathrm{h}} = k_{\mathrm{h}} z(t)$ is the restoring (buoyancy) force, with $k_{\mathrm{h}} \in \mathbb{R}^{n_{\mathrm{DoF}} \times n_{\mathrm{DoF}}}$ the hydrostatic stiffness, and $f_r = h_r \star \dot{z}$ is the radiation force, with $h_{\mathrm{r}}(t)$ the radiation impulse response kernel, with $\star$ the convolution operator. Finally, $M = m + m_{\infty}$, with $m \in \mathbb{R}^{n_{\mathrm{DoF}} \times n_{\mathrm{DoF}}}$ being the mass of the WEC, $m_{\infty} = \lim_{\omega \to \infty} A_{\mathrm{r}}(\omega)$, and n_{DoF} the number of DoFs considered (two in this case). $A_{\mathrm{r}}(\omega)$ and $B_{\mathrm{r}}(\omega)$ are the so-called radiation added-mass and damping, respectively, defined from Ogilvie's relations (Ogilvie 1964), from which $h_{\mathrm{r}}(t)$ can be computed.

Several approaches to computing the optimal PTO force can be found in the literature. As mentioned in the introduction, the idea behind CCD strategies is to consider the controller that will be implemented on the final device from the design stage. Such a controller should, ideally, be an advanced control strategy that optimises energy extraction, in order to minimise energy generation costs. However, given that this study focuses on comparing different global optimisation techniques, rather than obtaining the true optimal device geometry, a simpler reactive controller is considered here, since it is not expected to significantly vary the final results, while reducing computational complexity. Thus, the control force is defined as,

$$f_{\mathrm{PTO}}(t) = k_{\mathrm{pto}} z(t) + b_{\mathrm{pto}} \dot{z}(t), \tag{2}$$

with $k_{\mathrm{pto}} \in \mathbb{R}^{n_{\mathrm{DoF}} \times n_{\mathrm{DoF}}}$ and $b_{\mathrm{pto}} \in \mathbb{R}^{n_{\mathrm{DoF}} \times n_{\mathrm{DoF}}}$ being the PTO stiffness and damping values, respectively. Note that both k_{pto} and b_{pto} are optimised for each considered sea state.

To provide the global optimization algorithms with hydrodynamic coefficients for every geometry tested, the coefficients are initially obtained using a boundary element method solver for a subset of geometries. Subsequently, an interpolation technique is employed to obtain the coefficients for the remaining geometries. The interested reader is referred to (García-Violini et al. 2023) for more information on the considered interpolation method.

2.2 *CCD methodology*

Generally, it is possible to formulate the WEC CCD scheme as

$$\rho^{\mathrm{opt}} \leftarrow \begin{array}{lll} \underset{\rho \in \mathbb{R}^N}{\text{Optimise}} & & \Psi(\rho) \\ \text{subject to:} & \underset{\substack{\hat{\mathrm{f}}_{\mathrm{u}} \in \mathbb{R}^N \\ \mathcal{C}}}{\max} & J_N(\rho). \end{array} \tag{3}$$

In this case, the optimisation problem aims to minimise the objective function Ψ with respect to the variable ρ, while adhering to a set of constraints. It should be noted that the structure of the objective function Ψ is contingent upon the unique specifications and needs of the application. In this analysis, the objective function Ψ encompasses the economic evaluation of each WEC configuration ρ.

Traditionally, the LCoE indicator is used as a reference to assess the commercial viability of power production projects, particularly in the renewable energy sector. Thus, given that the CCD strategy aims at improving the commercial viability of the considered WEC, it is convenient to use the LCoE as the cost function for the optimisation, defined as

$$\mathrm{LCoE} = (\mathrm{CapEx} + \mathrm{OpEx})/\mathrm{EP}, \tag{4}$$

measured in €/Wh, where CapEx stands for capital expenditure, OpEx for operational expenditure and EP for energy production over its lifetime. However, for the objective pursued in this study, a simpler and more pragmatic function is sufficient. In particular, OpEx is assumed to be a proportion of CapEx, with the latter being calculated solely based on the mass of the floater (assuming that the material is steel). Thus, the alternative LCoE considered here (termed LCoE*) is defined as,

$$\mathrm{LCoE}^* = ((1 + \mu_{\mathrm{OpEx}}) \mathrm{c}_{\mathrm{steel}} m)/\mathrm{EP}, \tag{5}$$

with μ_{OpEx} the proportion considered to define the OpEx as a function of the CapEx and $\mathrm{c}_{\mathrm{steel}}$ the cost of steel per kilogram.

3 GLOBAL OPTIMISATION ALGORITHMS

From the CCD formulation proposed in Section 2.2, the question arises as to which global optimisation algorithm is the most suitable for the current problem. Various AI-based approaches have been proposed in the literature, each with its advantages and disadvantages. The aim of this paper is to test some of the most commonly used AI-based algorithms to determine which approach is the most suitable. The selected algorithms for the present study include the genetic algorithm (GA), the pattern search algorithm (PS), the particle swarm optimisation algorithm (PSO) and the surrogate optimisation algorithm (SO). Such techniques are briefly introduced in the following subsections.

3.1 *Algorithm 1: Genetic algorithm*

Genetic algorithms (Holland 1992) are optimisation techniques inspired by the process of natural selection and genetics. They are based on the principles of evolution and use a population of candidate solutions, often represented as chromosomes or strings of parameters. The algorithm iteratively evolves this population through a process of selection, crossover and mutation to find the optimal solution.

In the initialisation phase, an initial population of candidate solutions is randomly generated. Each candidate solution is evaluated based on a fitness function, which quantifies its performance as a function of the optimisation objective. During the selection phase, individuals from the population are selected for reproduction based on their fitness values, with higher-fitness individuals having a higher chance of being reproduced. The selected individuals then undergo crossover and mutation operations to produce offspring, which inherit characteristics from their parent solutions.

Crossover involves exchanging genetic material between pairs of parent solutions to create new candidate solutions, while mutation introduces random changes to the offspring solutions. The offspring solutions replace some individuals in the current population, and the process repeats for a certain number of generations or until a termination criterion is met.

Genetic algorithms are particularly useful for optimisation problems with complex fitness landscapes. They can efficiently explore diverse regions of the search space and handle non-linear and non-convex objective functions. However, they may require careful tuning of parameters and can be computationally expensive for certain problems. In the wave energy context, GAs have already been suggested in (Zarketa-Astigarraga et al. 2023, Zarketa-Astigarraga et al. 2023) for optimising air turbine geometries of oscillating water column WECs.

3.2 *Algorithm 2: Pattern search algorithm*

Pattern search algorithms (Lewis & Torczon 1999) are derivative-free optimisation techniques that explore the search space by systematically probing promising regions based on patterns or directions. Unlike gradient-based methods, pattern search algorithms do not require explicit knowledge of the objective function derivatives and are suitable for non-smooth and non-convex optimisation problems.

In pattern search algorithms, the search begins from an initial solution and iteratively moves towards better solutions by evaluating the objective function at nearby points. The algorithm maintains a set of search directions or patterns, which determine how the search progresses in each iteration. These patterns can be predefined, such as orthogonal axes directions or randomly generated directions.

At each iteration, the algorithm evaluates the objective function at candidate points along each search direction and updates the current solution based on the best-performing candidate. The step size or magnitude of the update can be adjusted dynamically based on the algorithm's progress and convergence criteria.

Pattern search algorithms are robust and versatile, capable of handling noisy, discontinuous and highly nonlinear objective functions. They are also well-suited for problems with constraints, as they do not rely on gradient information. However, they may require a larger number of function evaluations compared to gradient-based methods, especially in high-dimensional spaces, and their convergence properties can vary depending on the choice of search directions and step size.

3.3 *Algorithm 3: Particle swarm optimisation*

Particle swarm optimisation (Wang et al. 2018) is a population-based optimisation technique inspired by the social behaviour of bird flocking or fish schooling. In PSO, candidate solutions, called particles, move through the search space to find the optimal solution cooperatively.

Each particle represents a potential solution to the optimisation problem and has a position and velocity vector in the search space. The position of each particle corresponds to a potential solution, while the velocity vector determines how the particle moves in the search space.

During the optimisation process, each particle adjusts its velocity based on its previous velocity, its distance to the best solution it has encountered (personal best) and the distance to the best solution found by any particle in the population (global best). This update is influenced by inertia, and cognitive and social components, which control the exploration and exploitation abilities of the algorithm.

Particles move towards promising regions of the search space by updating their positions based on their velocities. The process continues iteratively until a termination criterion is met, such as a maximum number of iterations or reaching a satisfactory solution.

Particle swarm optimisation is known for its simplicity, ease of implementation, and fast convergence. It is particularly effective for continuous optimisation problems with smooth and convex objective functions. However, PSO may struggle with multi-modal and highly non-linear objective functions, and its performance can be sensitive to parameter settings.

3.4 *Algorithm 4: Surrogate optimisation*

Surrogate-based optimisation techniques (Queipo et al. 2005), also known as response surface methodologies, are iterative optimisation methods that leverage surrogate models to approximate the behaviour of the objective function. Instead of directly evaluating the expensive objective function, surrogate-based optimisation builds a computationally inexpensive surrogate model based on a limited number of function evaluations.

In surrogate-based optimisation, the algorithm starts with an initial design of experiments (DoE), consisting of a small set of candidate solutions evaluated using the true objective function. Based on the initial DoE, a surrogate model, such as a polynomial regression, Gaussian process or neural network, is trained to approximate the objective function behaviour over the entire search space.

Once the surrogate model is trained, the optimisation algorithm uses it to guide the search for promising regions of the search space. The algorithm iteratively selects new candidate solutions based on an acquisition function, which balances exploration (sampling in unexplored regions) and exploitation (sampling in regions with high predicted performance).

After evaluating the objective function of the selected candidate solutions, the surrogate model is updated to incorporate the new information. This process also continues until a termination criterion is met.

Surrogate-based optimisation techniques are particularly useful for optimisation problems with expensive, black-box objective functions that are computationally prohibitive to evaluate directly. They can significantly reduce the number of function evaluations required to find an optimal solution and are well-suited for optimisation under uncertainty or noisy environments. However, the accuracy of the surrogate model and the choice of acquisition function can influence the algorithm's performance, and careful consideration is needed to ensure reliable results.

4 CASE STUDY

In this section, an illustrative example is presented to show the advantages and disadvantages of the different optimisation algorithms for the CCD approach presented in Section 2.2.

4.1 *Realistic Climate*

In order to compute the energy produced by the WEC over its lifetime (see Section 2.2), the consideration of various sea states is necessary to assess its performance on a specific site. These sea states are selected based on the probability distribution of their occurrence at the designated site, a representation commonly depicted using a scatter diagram (Barstow et al. 2008). It is important to note that energy production over a whole lifetime of 20 years is computed, based on past wave data of the selected location.

For this study, the chosen location is BIMEP, a near-shore test site located in the Bay of Biscay off the Basque coast. In order to include the information of the site within the considered CCD problem, it is necessary to characterise the wave conditions of the given site with a finite number of sea states. To this end, the 8 most relevant sea states (from an occurrence probability perspective) have been chosen in this analysis, as shown in Figure 1(Zarketa-Astigarraga et al. 2023). That way, the authors aim to cover the whole operational region of the WEC at the selected location in a computationally efficient manner (Zarketa-Astigarraga et al. 2023).

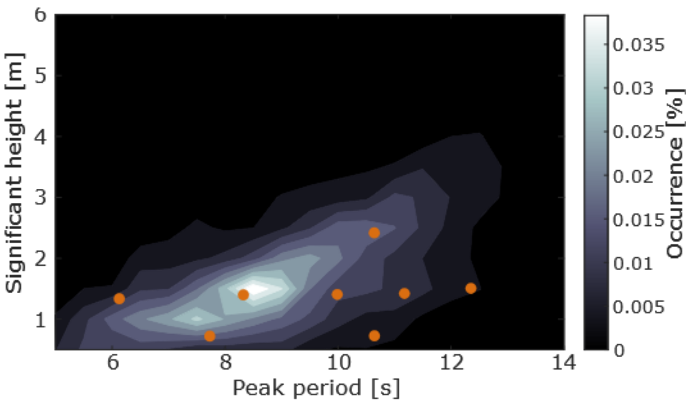

Figure 1: The 8 chosen sea states (orange dots) over the scatter diagram of the wave conditions at BIMEP.

Additionally, in order to be statistically consistent, the results for each of the selected sea states are derived by averaging the outcomes across several realisations of each sea state.

4.2 *WEC device*

The WEC considered for this study is inspired by the CETO WEC developed by Carnegie (Rafiee & Fiévez 2015). As introduced in Section 2.1, the device is considered to move in surge and heave only. The two parameters to be optimised in the considered WEC are its height and diameter (see Figure 2). Note that the distance from the still water level to the centre of the device (H_d) is kept to a constant value of 6.5 meters, regardless of the height of the device. The considered height and diameters range from 2.5 to 7.5 meters and from 12.5 to 37.5 meters, respectively. In this case, the hydrodynamic coefficients are computed for 7 different heights and diameters (along with their combinations) and, as further detailed in Section 2.2, an interpolation procedure is applied within the CCD framework to get the hydrodynamic parameters for all the cases. For further information on the considered method, the reader is referred to (García-Violini, Peña-Sanchez, Zarketa, & Penalba 2023).

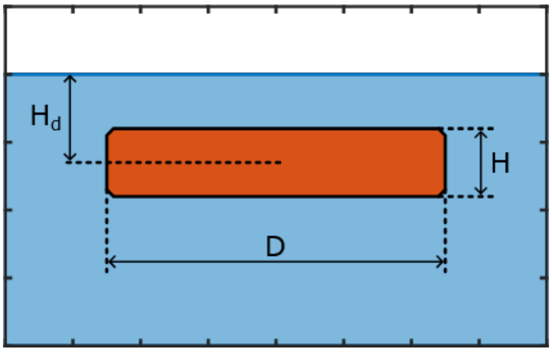

Figure 2: Sketch of the considered CETO-like WEC.

In order to compute the LCoE*, it is assumed that the cost of the steel is $c_{steel} = 0.72$/kg and that the OpEx correspond to a 30% of the CapEx (i.e. $\mu_{OpEx} = 0.3$).

5 RESULTS AND DISCUSSION

This section provides an overview of the results obtained with the different ML-based global optimisation techniques for the case study described in the previous section. It should be noted that the results shown in this section have been obtained by manually finding the best set of hyperparameters for each ML-based optimisation technique.

First of all, and in order to better understand the current optimisation problem, Figure 3 shows the LCoE* computed for a number of diameter and height combinations within the range considered in this study. In particular, the diameters are discredited every 0.5m and the heights every 0.2m (to obtain a similar set of points for each variable). For this brute-force approach, the optimum LCoE* point is 56.63, obtained for H=3.7m and D=12.5m, but these would change depending on the selected discretisation.

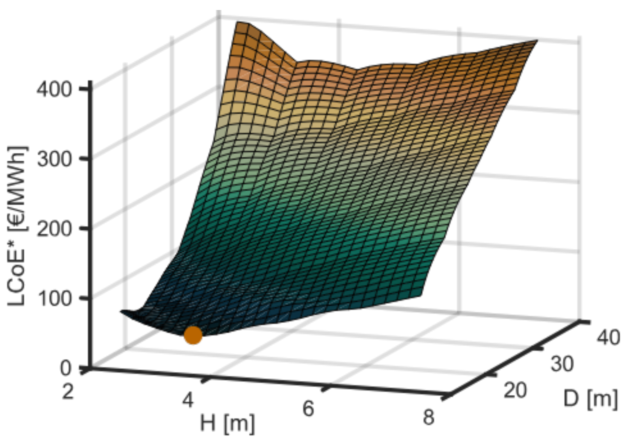

Figure 3: Surface plot of the entire considered function space obtained with a brute-force approach for the 10 realisations case.

Then, an analysis of how the complexity of the problem affects the time required by each optimisation technique is carried out. To this end, the effect of considering different wave realisations is analysed (see Section 4.1). Figure 4 shows the computational time required by each technique as a function of the number of realisations considered and normalised by the quickest case for each optimisation technique. Despite the small differences among the different techniques, it is clear that all of them are affected similarly and the time required to obtain a solution increases (almost) linearly when increasing the number of realisations (i.e. with the cases analysed). However, it should be noted that, when adding variables to be optimised, the number of cases grows exponentially, and so does the time required to solve the problem.

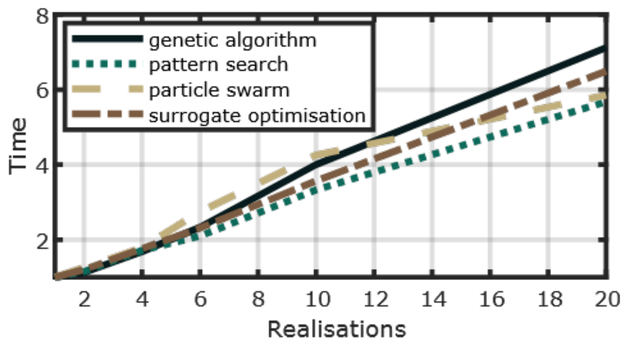

Figure 4: Computational time required by each optimisation technique as a function of the number of realisations considered, normalised by the quickest case of each approach (i.e. the single realisation case).

Regarding the time required by each optimisation technique, Table 5 shows the computational requirements for all the cases, normalised by the quickest case among all the techniques. The results show that the pattern search algorithm is the quickest overall, requiring 38 seconds[1] to obtain the results for the single-realisation case (the rest of the times in Table 5 are normalised using this case as the reference case). In summary, among the analysed methods, PS is shown to be the most computationally efficient algorithm, with the SO and PSO algorithms being one order of magnitude slower. The GA is demonstrated to be the slowest approach, being two orders of magnitude slower than PS.

The last row of Table 5 displays the time required to compute all the results using the brute-force approach, as illustrated in Figure 3. It is important to note that while the brute-force approach may not appear significantly slower than the proposed optimisation algorithms, this can be attributed to the coarse discrimination employed in the brute-force method, which utilises a single decimal point. In contrast, the optimisation approaches utilise finer discrimination with two decimal points.

[1] Computational requirements are measured on a laptop with a 7^{th} generation Intel i7 processor and 12GB DDR4 RAM.

Table 1: Normalised computational time required by each optimisation technique for different numbers of realisations.

	Realisations					
	1	2	4	6	10	20
GA	42.3	47.9	71.2	98.8	170	302
PS	1[a]	1.2	1.7	2.1	3.3	5.7
PSO	10.1	12.7	18.1	27.8	43.1	59.3
SO	3.2	3.9	5.7	7.5	11.5	21
BF[b]	19.8	23.5	35.7	48.5	73.6	136.4

[a] 1 = 38 seconds.

[b] Discretisation is an order of magnitude lower

The GA is much slower because it considers a wider range of scenarios compared to the other methods. However, the WEC CCD problem of this analysis does not pose a very complex problem where many possible combinations must be tested in order to ensure that the solution is not a local maximum or minimum point. Thus, techniques like PS or SO which follow a trajectory in order to find the maximum/minimum point might be more beneficial.

For illustrative purposes, Figure 5 shows how each optimisation technique converges to the obtained result.

Finally, the results obtained by each solver are shown in Table 5 showing that they all converge to (almost) identical results. However, it is worth highlighting that the PS algorithm does not find the same results as the rest, always stopping slightly before reaching the real optimum combination. However, due to its speed, it may be a useful tool to compute initial results and reduce the search space for a more sophisticated algorithm.

Table 2: Optimal diameter, height, and LCoE* obtained with the different optimisation techniques for the 10 realisations case.

	Results		
	H	D	LCoE*
GA	3.63	12.50	56.49
PS	3.64	12.52	56.59
PSO	3.63	12.50	56.49
SO	3.63	12.50	56.49

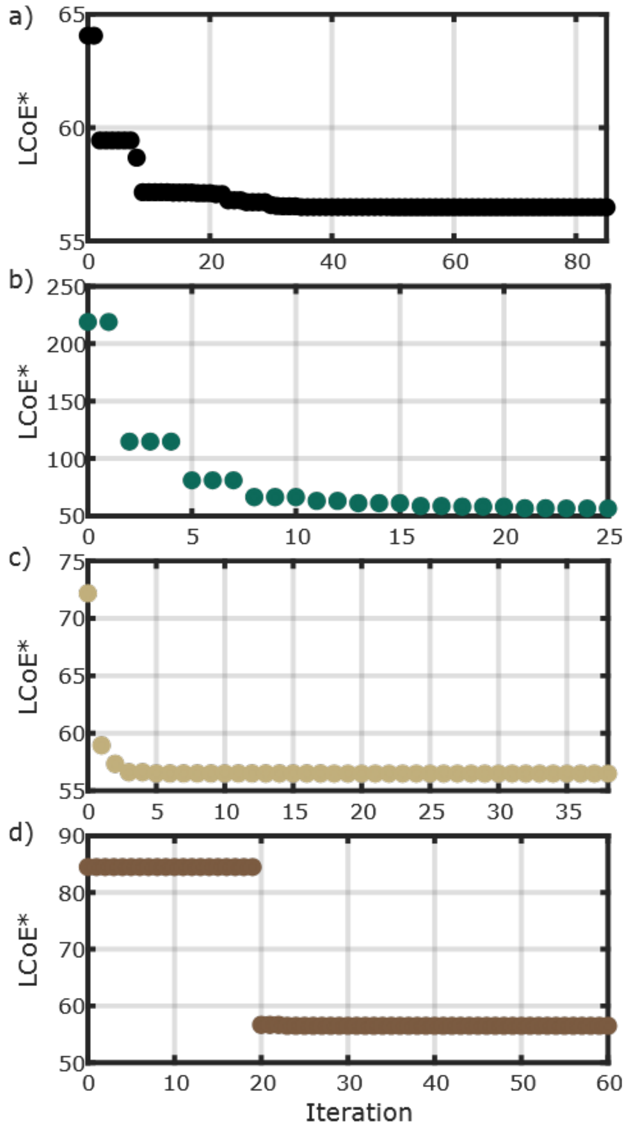

Figure 5: Considered iterations and convergence to the final LCoE* for the different optimisation techniques: (a) GA, (b) PS, (c) PSO and (d) SO.

The results also suggest that optimisation techniques that rely on trajectory-based optimisation strategies, such as pattern search and surrogate optimisation, may offer advantages over techniques that explore a large number of combinations, such as genetic algorithms. These trajectory-based techniques appear to be particularly well-suited for the nature of the WEC CCD optimisation problem, enabling them to efficiently navigate the solution space and avoid running large number of combinations to avoid local minimum or maximum points.

While the present study provides valuable insights into the performance of different optimisation techniques for WEC CCD, it is important to acknowledge certain limitations. For instance, the analysis focuses on a specific case study of a two-degree-of-freedom cylindrical WEC, and the results may vary for different WEC configurations or operating conditions. Future research could explore these techniques in broader contexts and investigate additional factors that may influence their performance.

6 CONCLUSIONS AND FUTURE WORK

This study aims at comparing four different global optimisation techniques for wave energy converter (WEC) control co-design (CCD) approaches: genetic algorithm, pattern search technique, particle swarm optimisation, and surrogate optimisation.The results of the comparison demonstrate that all four optimisation techniques converge to very similar results, in a fraction of the time required by a brute-force optimisation approach. This finding underscores the potential of these techniques to significantly accelerate the design and optimisation process for WECs.

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