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Review article

Layout and design optimization of ocean wave energy converters: A scoping review of state-of-the-art canonical, hybrid, cooperative, and combinatorial optimization methods

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ABSTRACT

Ocean Wave energy is becoming a prominent technology, which is considered a vital renewable energy resource to achieve the Net-zero Emissions Plan by 2050. It is also projected to be commercialized widely and become a part of the industry that alters conventional energy technologies in the near future. However, wave energy technologies are not entirely yet developed and mature enough, so various criteria must be optimized to enter the energy market. In order to maximize the performance of wave energy converters (WECs) components, three challenges are mostly considered: Geometry, Power Take-off (PTO) parameters, and WECs' layout. As each of such challenges plays a meaningful role in harnessing the maximum power output, this paper systematically reviews applied state-of-the-art optimization techniques, including standard, hybrid, cooperative, bi-level and combinatorial strategies. Due to the importance of fidelity and computational cost in numerical methods, we also discuss approaches to analyzing WECs interactions' developments. Moreover, the benefits and drawbacks of the popular optimization methods applied to improve WEC parameters' performance are summarized, briefly discussing their key characteristics. According to the scoping review, using a combination of bio-inspired algorithms and local search as a hybrid algorithm can outperform the other techniques in layout optimization in terms of convergence rate. A review of the geometry of WECs has emphasized the indispensability of optimizing and balancing design parameters with cost issues in multimodal and large-scale problems.

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1. Introduction

Nowadays, due to the necessity of investigating ocean renewable energies, particularly wave energy, which has great potential for energy harnessing, there is an ever-increasing need for research in this area. As such, the number of publications on this subject has skyrocketed over the last two decades. Although the reasons for the increased interest may be environmental and financial, the capacity to extract energy from optimized wave energy converters has been enhanced compared to a non-optimized array of WECs. Researchers apply optimization methods to various aspects of the project, from determining the best installation location to minimizing the Levelized cost of energy (LCOE) (Heravi et al., 2020; Korzeniowski et al., 2021; Ghorbani and Korzeniowski, 2020). The optimization methods can firstly be used to identify potential locations for extracting more power from incident waves. After selecting the type and model of WEC, the shape and dimensions of the converter can be optimized. Following that, capturing more power necessitates the use of optimal Power Take-Off parameters and the selection of an effective control strategy for a chosen WEC (Jusoh et al., 2021), which has a high priority in the European countries. The mooring and foundation of such structures are challenging in which to find the optimal design.

One of the most critical optimization problems of exploiting wave energy projects is the configuration of the WECs in an array because the interaction and coupling effects between the converters and water may have a direct relationship with the power output of the array. Researchers have even attempted to optimize the q-factor (a factor determining whether the interactions are effective or destructive) in order to achieve the optimal configuration and maximize the power output (Göteman et al., 2018). Apparently, other issues in between were taken into account to benefit from finding the optimal solution.

The problems of extracting renewable energy from waves (using various wave energy converters, particularly point absorbers) have been predominately solved over the last three decades. The literature shows that most case studies have been published based on potential locations to assess the probability of harnessing energy. The importance of finding the optimal solution to the related problems has recently motivated researchers to focus on this issue. In fact, not only has the interest in optimizing studies increased but also has the interest in solving problems using Computational Fluid Dynamics (CFD) methods (Dafnakis et al., 2020).

In recent years, many papers have been published on the optimization problem of wave energy converters, with the majority modifying and applying metaheuristic optimization algorithms such as Genetic Algorithm (GA) (Lyu et al., 2019), Differential Evolution (DE) (Gomes et al., 2012), gradient descent (Abraham and Kerrigan, 2012), and Simulated Annealing algorithm (SA) (Liu et al., 2020a). Many factors must consider in renewable energy exploitation. The projects of wave energy converter array have many aspects, such as lifetime cost, Capital Expenditure (CAPEX), LCOE, environmental impact, maintenance, and others. However, The maximum power output of the array is the most intriguing parameter for increasing revenue from energy extraction, so researchers have tried to benefit the optimization technique to harness more power.

This paper aims to review articles that investigate the optimized configurations of an array of WECs, regardless of whether the optimized fitness function is directly developed for this purpose or not, in the form of a scoping review. As its name implies, scoping study provides a thorough understanding of the extent and scope of literature on a given topic, as a comprehensive summary of the body of literature, and provides an overview (in-depth or broad) of its focus. There are certainly merits in doing a scoping review when it is not clear what other, more specific questions could be asked and analyzed through a more specific systematic review (Armstrong et al., 2011; Munn et al., 2018; Rahgooy et al., 2022). To this end, we attempted to discuss particular aspects of wave energy problems, such as analyzing a single WEC and interaction effects, in a brief manner. Before arguing approaches to analyzing a wave energy converter and discussing interaction resources and parameters, we begin the paper by looking at six types of converters, followed by an argument over worldwide projects and related case studies. Following that, we classified metaheuristic optimization-related articles based on the scientific community's interest. We provide a review of the PTO system, the geometry of a WEC, as well as regular and arbitrary patterns in three parts.

The structure of this article is outlined as follows. Section 1 introduces the classifications for WECs, then provide an overview of influential case studies and projects in different countries. Section 2 enumerates the implementation techniques for selecting the numerical hydrodynamic model and also mentions the optimizing methods by classifying meta-heuristics into three classes: global optimization, local optimization, and local techniques. Section 3 introduces the recent technologies and heuristic optimization methods used in the fields, followed by a more in-depth look at the layout configuration, Power Take-off advancements, and geometry of a WEC. Section 4 gives directions and research gaps to the researchers in this field. Finally, Section 5 concludes the main outcomes of the paper.

1.1. Classification criteria

Salter et al. (1974), who studied wave power and discussed its potential, pioneered wave energy conversion and the installation of various WECs in 1973. Later, academia and a number of institutions set aside funds to facilitate the research.

Fig. 1 shows that in the 1970s, researchers became interested in the field of ocean wave energy using the largescale

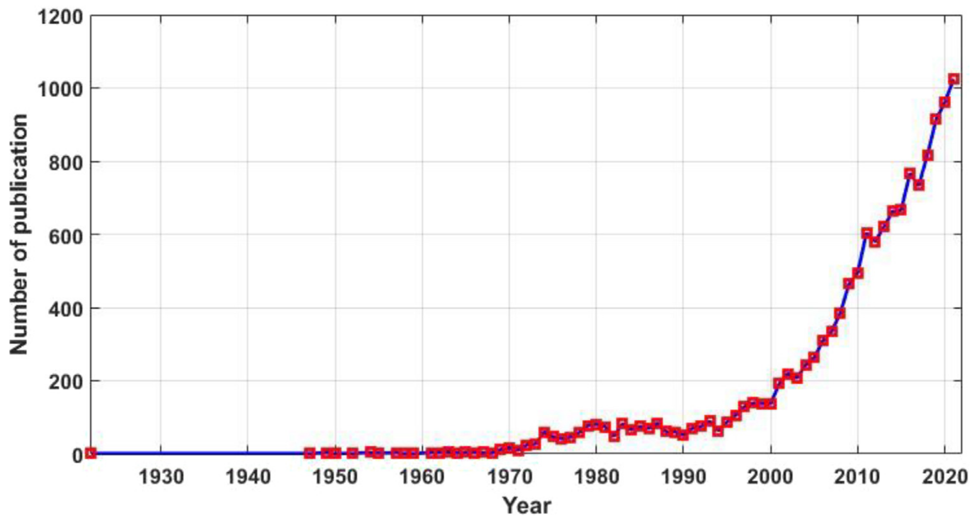


Fig. 1. The statistical results of published papers in the field of 'ocean wave energy' between 1922 and 2021 based on the SCOPUS (2021).

document-level of the significant bibliographic data source (SCOPUS, 2021) and based on exploring the keywords 'ocean wave energy'. However, since the beginning of the twenty-first century, the number of documents in this field has significantly increased. Fig. 2 represents the number of publications by ten prestigious journals in this field from 1974 to 2020. Between 2000 and 2002, the Journal of Physical Oceanography published approximately 70 papers that made notable contributions to academia. Other journals, such as Renewable Energy and Ocean engineering, have published numerous articles in this field during the last three years. According to the published papers, various subjects such as earth and planet, engineering, and energy are most interested among researchers, as shown in Fig. 3. Furthermore, most mentioned subjects are articles and conference papers, while review papers contain only 2.3% of all published studies.

To this day, there are at least six well-known classifications of converters based on the installation location, type, principle of PTO system, working principles, floating or submerged, and degree of freedom (DOF) number. Fig. 4 demonstrates some of this classifications. Based on their definitions, the last two items are easy to follow because they are either floating, fully submerged, partially submerged structures, or placed on the seabeds. There are also six degrees of freedom that can be divided into two parts. The first part contains rotational degrees, including roll, pitch, and yaw DOF, and the second contains translational degrees, including heave, sway, and surge. Fang et al. (2020) investigated a double-degree-of-freedom wave energy converter that can absorb higher energy than a single degree of freedom. The WECs can be classified based on the Degree of Freedom (DoF) they have. It should be noted that a few of WECs are hybrid such as (Ren et al., 2020) that experiments with the concept of a combination of tension leg platform wind turbine with a heaving wave energy converter. In order to account for the recent improvements in hydrokinetic systems, Ibrahim et al. (2021) reviewed hydrokinetic energy harnessing technologies by studying the state-of-the-art energy systems in the sea- and river-based applications. Below is a brief description of similar informative classifications of WECs.

(i) Location: There are three parts to the installation site for converters. Onshore systems are WECs built along the shoreline or attached to constructed structures such as breakwaters. Moreover, Nearshore devices are placed at a depth of 10 to 25 m, 500 to 2000 meters from the shoreline. Nearshore has Limited bathymetric zones, around a quarter wavelength. Finally, offshore systems, which range in depth from 40 meters to over 100 m, make selecting an adaptable converter to withstand deep water incoming waves challenging (López et al., 2013; Babarit, 2017).

(ii) Type: The proportion of WECs' dimension to wavelength, as well as their direction to the incident wave, can be classified into the following categories. Attenuators are large, float-on-the-water devices oriented parallel to the wave direction. The next one is terminators, which are installed perpendicular to the predominant wave direction and have a regular size greater or equal to the wavelength. The last type is point absorbers, a smaller device than others and has a shorter incoming wavelength. They can be either floated or submerged converters (Drew et al., 2009; Aubry et al., 2011).

(iii) Principle of PTO system: The PTO system is one of the most substantial parts of a WEC. Therefore, various methods have been used to produce electricity. Hydraulic motors, turbines with WECs, and electrical drive-based systems are well-known PTO system methods (Wang et al., 2018). Ahamed et al. also stated that other PTO systems, such as direct mechanical drive systems, triboelectric nanogenerators, and hybrid systems, have recently been used. The working principles of each PTO system are different from others. For instance, some have an air chamber and convert power from air pressure, especially the Wells turbine and impulse turbine. Another type, on the other hand, has hydraulic oil to drive the motor for generating power (Ahamed et al., 2020).

(iv) Working principles: WECs can be classified into three types based on their functionality, as can be seen in Fig. 5. The first is overtopping devices, which absorb energy from waves passing over a ramp that fills a higher level basin or reservoir before releasing the stored water into the sea. The second type is the oscillating water column (OWC). It consists of an air turbine and a chamber with two openings at the bottom and above. The rise in the water compresses the air in the air turbine to produce energy. The last one is wave-activated bodies, which generate power from the motions of the converter caused by the waves (Babarit, 2017). In this classification, mainly introduced by Falcao (Antonio, 2010), both the PTO system and floating or submerged structures were divided. Different types of hydromechanical conversion are proposed to classify the three mentioned. This has two Rotating generators with or without energy smoothing, hydro-pneumatic

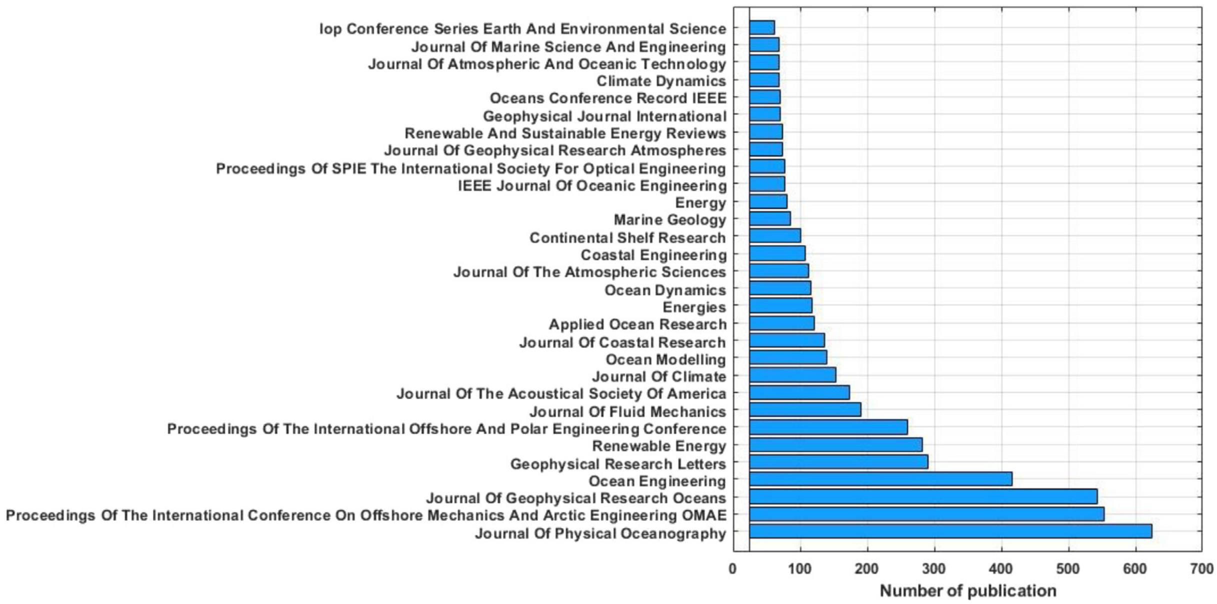


Fig. 2. The most number of published papers by the top 20 scientific journals in the field of 'ocean wave energy' from 1974 to 2021 based on SCOPUS (2021).

or oleo-pneumatic conversion system, and by electrical generator directly or indirectly from the movement. More information about the hydro-mechanical conversion types is described in Section 3.2.

1.2. Influential case studies

In recent years, countries contributed to publishing documents related to ocean wave energy. However, based on Fig. 6, few of these countries' researchers published more than 500 research articles. The United States has worked on this subject and published over 4000 documents, outnumbering China's 1700 papers by far. It should also be noted that institutions can assist academia increase the number of studies. For instance, the Chinese Academy of Sciences and Scripps Institution of Oceanography have collaborated to publish over 600 documents, while the University of Washington Seattle has published approximately 320 papers. Institutions that receive government or private funding can play a vital role in both the industry and academic society.

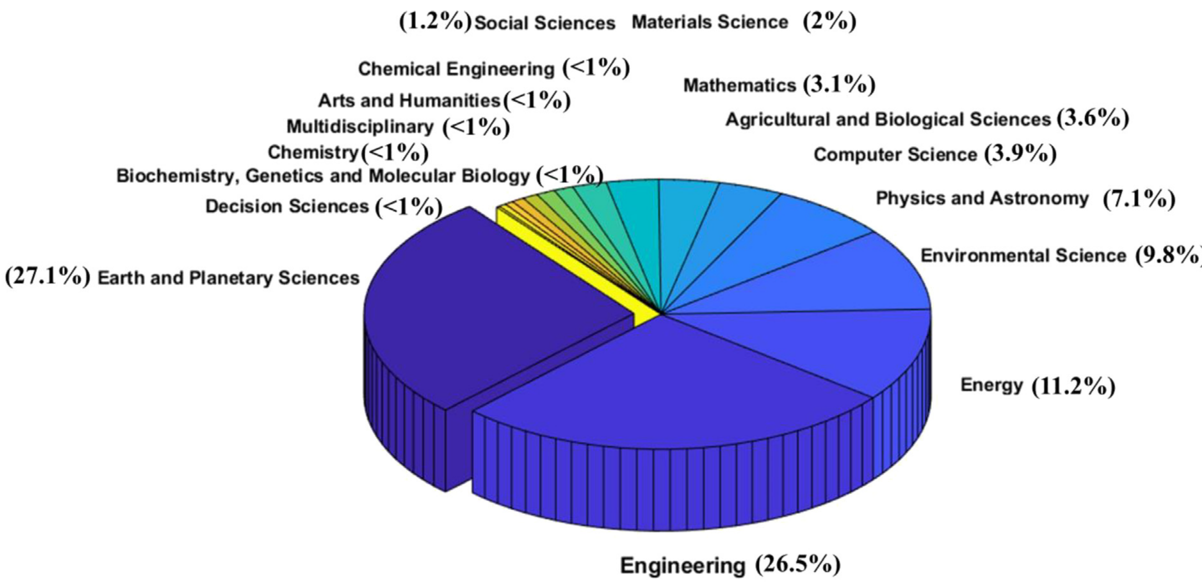
This increase in the number of publications led to the initiation of large projects by countries and companies around the world. Although a few of them in the recent years working productively, in 2019, the ocean energy sector encountered some obstacles, including the sinking of the Wello's Penguin WEC (Energy global news, 2019) and the termination of the Western Australian government's contract with Carnegie due to the developer's financial difficulties (ABC News, 2019).

Nonetheless, the sector is ripe for technological advancement. The devices currently in use have increased survivability by operating throughout the year under extreme marine conditions; However, due to the limited amount of electricity generated by WECs so far, most devices are still in the pre-commercial phase. Improvements must be made in matters such as WEC design optimizations, the validation of PTO reliability, and proposed LCOE targets. In particular, Wave energy extraction in Europe could reach 30 GW by 2050 under the European Strategic Energy Technology Plan cost-cutting scenario (Simoes et al., 2013; Luis Villate et al., 2020). Also, Scotland, the EU, and the United States have all provided research and development funding to projects aimed at developing low Technology Readiness Levels (TRL) technologies and innovative PTO systems since 2016 (Magagna, 2020).

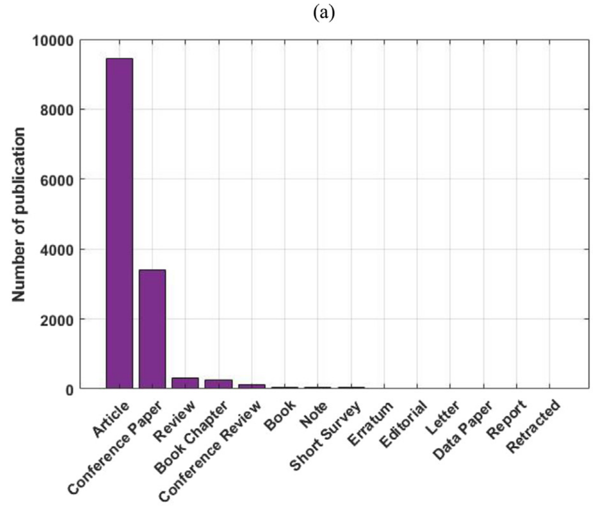
Since 2010, Europe has been the world leader in the wave energy sector, with the most full-scale wave energy devices and 1250 kW of capacity installed per year. Europe now has the opportunity to consolidate its lead and dominate a new global high-value market (Luis Villate et al., 2020). One of the main reasons for such progress in this industry not only is the mean annual energy potentially high in those locations but also a prospective vision of the EU facilitates the progress of exploiting renewable energy.

Since the Horizon 2020 (H2020) Framework program launch in 2014, the European Commission (EC) has funded 47 projects to improve various ocean energy technologies. Projects examples are the Waveboost project working on Corpower C3 device optimization, the LiftWEC project to explore the development of WECs concept based on the exploitation of lift forces generated by wave-induced water velocities, and the Opera project, which employed the Oceantec Marmok device in Spanish waters (Tethys, 2020). The Imagine Project aims to create a new Electro-Mechanical Generator intended for wave energy applications, which can reduce the CAPEX of current PTO technologies by more than 50% while increasing average efficiency to more than 70% and a lifetime to 20 years. The Wave Energy Scotland (WES) PTO program has already provided funding for this technology. The SEA-TITAN project seeks to design, build, test, and validate a direct drive PTO solution that can be used with various WECs. The majority of current wave energy research and development projects are centered on this critical aspect of WECs, the development of reliable PTO (Magagna, 2020).

Supporting such technologies also has been done at a national level. The United Kingdom was the first to set the goal of reaching net-zero emissions by 2050. In order to attain this objective, the UK Research and Innovation (UKRI) is currently funding eight projects to work on state-of-the-art wave energy technologies (UK Research and Innovation (UKRI), 2021). The main goals of these projects are to enhance the performance and survivability of WECs by developing and testing novel WEC generators, essential device controls and monitoring systems, a highly accurate modeling suite, and investigating the possibility of using new flexible materials for WECs. In addition, the UK established the WES, which has supported 90 research projects since 2014. Projects included novel device concepts, new materials, PTO, and control systems of wave energy devices (Ocean Energy Systems (OES), 2020).



(a)



(b)

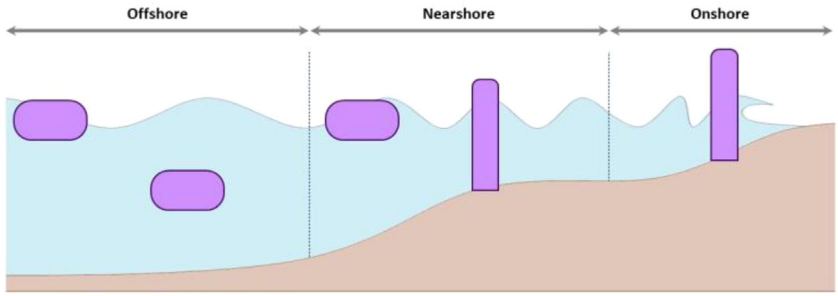
Fig. 3. The contribution percentage of (a) subject areas, (b) documents type in the field of 'ocean wave energy' (SCOPUS, 2021) based on the published Scopus papers between 1974 to 2021.

Corpower, a Swedish company, attracted almost 20 million Euros for a wave energy project in the northern part of Portugal. The first commercial-scale C4 Wave Energy Converter will be deployed off the coast of Agucadoura in 2021 as a part of a four-system WEC array. By noting extracting five times more energy per ton of device from an amplified power capture system, they hope to commercialize the technology till 2024 entirely. The point absorber converter uses Bodycote care in order to improve survivability and its resistance against collision (CorPower Ocean, 2019; ENERGY INDUSTRY REVIEW, 2021).

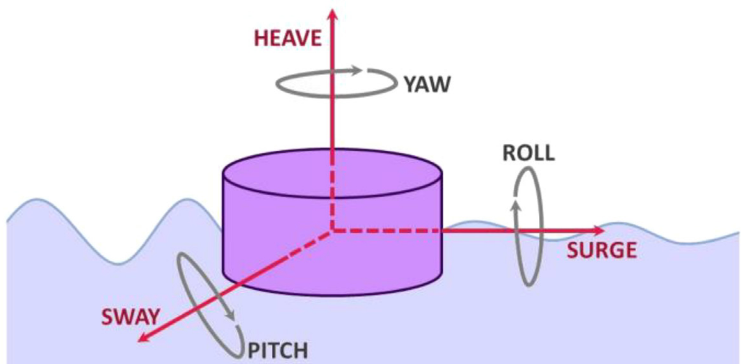
The Australian Renewable Energy Agency (ARENA) has funded Australian companies (Ocean Energy Systems (OES), 2020), including Bombora, to investigate the economics of a 60MW wave farm consisting of 40 Bombora WECs at a site near Peniche in Portugal which was completed in 2016 (Australian Renewable Energy Agency, 2020), Carnegie to develop the CETO6 device (which was canceled later in 2019) (Australian Renewable Energy Agency, 2021a) and the ongoing Wave Swell project to construct the UniWave200, a 200 kW WEC at King island (Australian Renewable Energy Agency, 2021b).

In China, Guangzhou Institute of Energy Conversion (GIEC) researched, developed, and designed Zhoushan, the first 500 kW Sharp Eagle WEC, assembled in Mazhou and deployed in WanShan Island, ZhuHai City in 2020. It is China's largest single-installed WEC (Chinese Academy of Sciences, 2020). Moreover, Li et al. (2022) studied the wave energy assessment in the southern South China Sea. They conclude that according to the influence of monsoons, the wave energy resources observe seasonal variations and Wave energy is higher and more stable in winter in this region.

California, Oregon, Washington, Alaska, and Hawaii have promising wave resources for WEC technologies in the United States. However, the Pacific Northwest's abundance of water supplies appears to be preventing widespread adoption in Washington and Oregon. The East Coast area has a less intense wave resource that may suit smaller-scale and distributed applications (LiVecchi et al., 2019). Alaska's wave resource is 890 TWh per year, which is almost 62% of the total available wave energy resource of the U.S (Kilcher et al., 2021). Various projects recently succeeded and currently expanding the absorption of wave energy by U.S. companies (The European Marine Energy Centre (EMEC), 2020). One of the companies currently working on wave energy extraction is Oscilla Power.



(a)



(b)

Fig. 4. Subfigure (a) shows the classification of placing wave energy converters in terms of their distance to the shore and their depth of deployment and (b) shows all possible degrees of freedom on a WEC (Babarit, 2017).

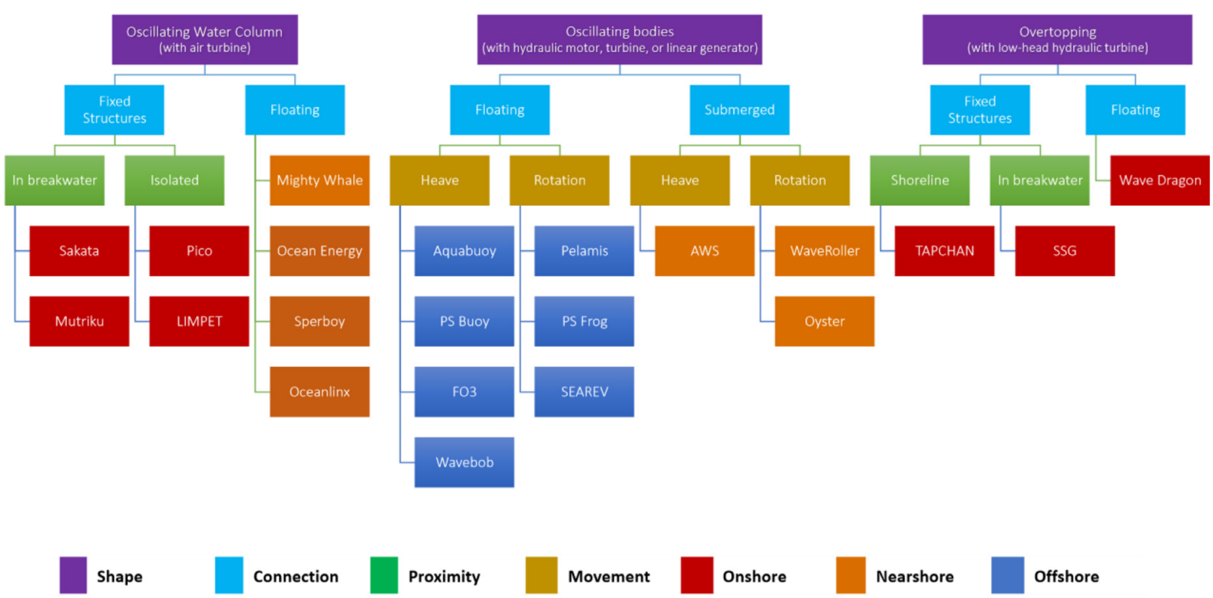
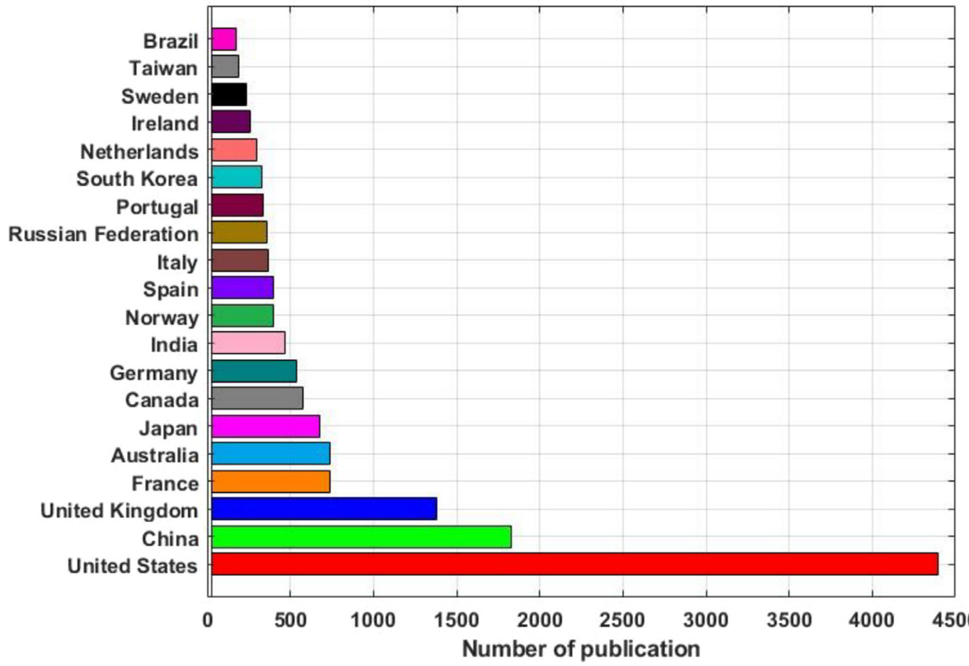


Fig. 5. Classification of wave energy converters based on their type, location, movement and connection.
Source: Adapted and reproduced from (Antonio, 2010).

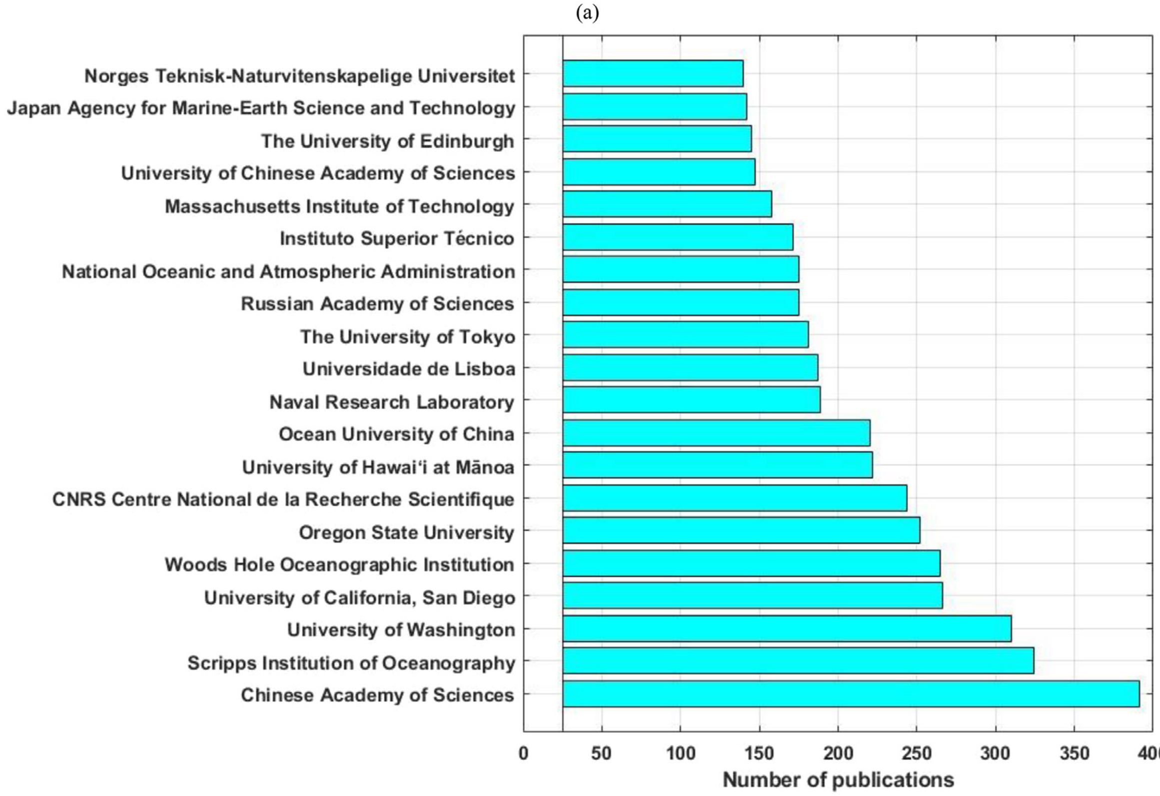
They are developing multi-modal point absorber WEC called Triton for large-scale arrays and Triton-C for remote communities, both of which can capture power from six DOF. The performance is validated via physical testing of different scales performed by the Department of Energy (DOE). This WEC has a low installation cost due to the use of flexible tendons (Oscilla Power, 2020; Ocean Energy Systems (OES), 2020).

2. Implementation techniques

At first, it is vital to choose the numerical hydrodynamic modeling method based on the desired fidelity for each project because computation time and cost are the crucial aspects of such research projects. Therefore, general classification and in-



(a)



(b)

Fig. 6. The sorted top (a) countries and (b) institutions with regard to the number of published documents in 'ocean wave energy' topic between 1974 and 2021 from SCOPUS (2021).

formation on each method can be helpful. There are several ways to simulate a WEC, which are different in terms of simulation time and fidelity. From lowest to highest simulation time, some approaches to modeling are mentioned. The most common methods among the researchers are potential flow (PF) based models, which itself is divided into four models (Folley et al., 2012).

- Linearized potential flow in frequency domain
- Semi-analytical techniques
- Linearized potential flow in time domain
- Nonlinear potential flow

The first approach is used in most of the studies, and its most popular solvers are WAMIT, NEMOH, ANSYS AQWA, based on the number of published articles. Regardless of limitations in the linearized method, researchers continue to use it, especially in small arrays because it returns valuable results in a short time (Babarit, 2010; Li et al., 2020b). The semi-analytical approach has been investigated by many researchers in this field. Some of the most popular solvers used in recent codes are direct matrix method from Kagemoto and Yue (1986), multiple body radiation and diffraction (Mavrakos, 1991), multiple scattering either iterative or non-iterative (Ohkusu, 1974; McNatt et al., 2015; Mavrakos and Koumoutsakos, 1987) and WEC-MS (Sergiienko, 2021). The difference between linearized potential flow in the frequency domain and time domain is that the latter has the ability to include transient effects and nonlinear external forces (Folley et al., 2012). Furthermore, nonlinear potential flow considers all non-linearity forces such as viscous drag, flow separation, vortex shedding, and other ones in this model (Penalba et al., 2017a).

When it comes to the numerical analysis of fluid flows, a branch of fluid dynamics called CFD can solve large and more challenging problems. To this day most accurate methods of solving Navier–Stokes equations are as follows. The most accurate method for considering small details is Direct Numerical Simulation (DNS). This method can remove any uncertainty induced by turbulence modeling. It solves all length and time scales of turbulence, so the accuracy of given results is high (Sandberg et al., 2015; Mozaffari et al., 2022). It should be noticed that from the reviewed papers, we did not find any solver based on this method. However, the chance of using such a method is going to increase with the ever-growing technology and supercomputers (Windt et al., 2018).

Large Eddy Simulations (LES) is the method that large-scale turbulent structure directly simulates and reserves the model for smaller-scale ones. This may increase the fidelity of the turbulent flow structure. The method tries to neglect the smallest length scale to reduce the computational cost compared to DNS. One of LES's theories is Smoothed particle hydrodynamics (SPH) which Liu recently used as a numerical model in prediction and optimization research (Liu et al., 2020b). Another method of solving Navier–Stokes equations is the hybrid approach RANS/LES. The combination of using two methods for equilibrium or nonequilibrium turbulence may have less cost than the LES method, and it can handle massively separated flows and it is more accurate than the RANS method (Georgiadis et al., 2010). Reynold-Averaged Navier–Stokes (RANS) approach is another one that can be defined as time-averaged equations of motions for fluid flow. Several popular tools are used for analysis of a WEC, such as STAR CCM+, OpenFOAM, SWENSE, and Fluent (Coe et al., 2016). As mentioned earlier, the accuracy of the RANS method is less than DNS and LES but faster to achieve the results (Devolder et al., 2018). In addition, Table 1 discusses the advantages and disadvantages of BEM, FEM, and FDM. And Table 2 briefly mentions the main differences between RANS, LES, and DNS methods and provides some of their drawbacks and merits.

Fig. 7 uses a tree diagram as an assessment tool to clarify the category of each method. Furthermore, several articles studied and solved the equations with the help of these methods. Table 3 shows some of the recent articles. It can be seen in the table that most of the papers have an inclination to analyze with linearized potential flow models rather than more accurate methods.

Going back to the factors considered in the literature to choose the appropriate method, some important factors are briefly discussed. First of all, the flow must be defined whether as laminar or turbulent. Secondly, in order to simplify the solving equations, flow can be considered incompressible, irrotational, or inviscid (Davidson and Costello, 2020). As an example, a linearized potential flow takes all three of them into account. According to Göteman et al. (2020) and Marchesi et al. (2020), the most common numerical method for hydrodynamic modeling is the Boundary element method (BEM) allowing to numerically solve the motions of WECs having different geometry and shape, with full consideration of wave interactions between bodies (Lyu et al., 2019).

In regards to BEM solvers, WAMIT is one of the many software for determining the interactions between offshore devices and waves. One of the advantages of this software is having an option to perform the high order boundary element method (HOBEM) to improve the computational performance (Tay and Venugopal, 2017). Moreover, NEMOH is an open-source solver based on BEM codes and has an advantage for the diffraction problem because the code can easily accommodate a user-defined distribution of normal velocities at the centroid of each mesh panel (Flavià et al., 2018). ANSYS AQWA is a multibody hydrodynamic program that utilizes three-dimensional radiation/diffraction theory for global loading and motion simulations (Ansys, 2013).

Although the introduced potential flow-based models are dominated by researchers in offshore studies, such methods may return unrealistic simulations in case of happening wave resonance because of overlooking viscosity effects (Göteman, 2017). Thus, viscous and turbulent effects can incorporate only by using CFD-based methods (Bharath, 2018). In fact, modelers use CFD tools for small-scale problems to avoid large computational costs and time.

2.1. Optimization methods

Meta-heuristics are considered black-box optimization algorithms extensively employed to find the best multiple optimal solutions (in a single run) out of all possible solutions in both science and industry. They evaluate potential solutions and implement a series of search mechanisms to them in order to generate different offspring and hope to converge on better solutions. Over the last decades, a large number of meta-heuristic algorithms have been developed to solve a wide range of real-world engineering optimization problems (Sörensen and Glover, 2013). We have classified meta-heuristics into three classes based on previous studies, including global optimization methods, local optimization methods and hybrid techniques.

Fig. 8 shows a diagram of meta-heuristic algorithms that were applied in order to improve the performance of various types of wave energy converters, including synergy (the original version of optimization methods without modifications) and hybrid techniques, which are a mixture of two or more number of optimization methods. Recently, the application of hybrid algorithms has been considerably increased in the field of wave energy system optimization compared with synergy algorithms. Hybrid optimizations decide which method should be applied in each iteration dynamically, and this candidate is selected from a pool of various optimization algorithms. They utilize a heuristic to anticipate the most effective algorithm in order to optimize each subsection of the whole computational budget.

Given the plethora of optimization methods and their implementations in related papers, various optimization methods have been proposed to improve the energy extraction capability of WECs. The given problem, the priority of main decision parameters, and the design of the objective function are all crucial in determining the best optimization practices.

2.2. Global optimization methods

Despite the fact that it is difficult to directly converge to the best solution in the majority of real engineering problems due to the existence of a large number of locally optimal solutions, it is relatively simple to use a numerical method and set up a loss

Table 1
The table indicates some of the positive and negative points of BEM, FEM, and FDM.
Source: The table is adapted from Yu et al. (2010).

	BEM	FEM	FDM
Merits	• Discretizing the boundaries • Lower computational cost • suitable to infinite problems	• Integration of simple functions • Easier modeling of complex geometries • Successful in Multi-physics analysis	• No numerical integration • easy to implement
Drawbacks	• Needs complicated integral relation • Shows difficulties in nonlinear and inhomogeneous problems	• Needs large data for mesh in terms of nodal connectivity • Needs integral relation • Time-consuming computations • Not good with infinite problems	• Not good with infinite problems • Fine grids • Domain mesh • Less accurate and more time-consuming than FEM

Table 2
The table shows some of the positive and negative points and also main differences between RANS, LES, and DNS.

	RANS	LES	DNS
Merits	• Needs small amount of points in transverse and smaller in longitude direction • Output is similar to a linear line in time	• Needs many points and time iteration • Reveal hidden eddies • Output is similar to a curve line in time	• Output is very similar to the experiments and fluctuates in time
Drawbacks	• Cannot do averaging in some phenomena • Not good with acoustic waves	• Massive parallel machine and important CPU time • Numerical technique which does not respects the dispersive and dissipative properties	• The most computational cost in commercial problems
Difference	• Navier–Stokes equations averaged in time • Implicit and low order	• Navier–Stokes equations filtered in space • High order scheme and small-time steps	• High order scheme (over than 6) and small-time steps

function that measures the quality of a feasible solution because this involves using some version of derivative of functions (Nocedal and Wright, 2006). For instance, one of these algorithms is gradient descent which minimizes the cost function as far as possible.

There are several works in the literature that employed investigated numerical methods. For instance, Noad and Porter (2015) adopted a multi-dimensional numerical optimization procedure for single flap-type OWSC to evaluate the solution method's accuracy and then to set up optimal device parameters for array optimization. To obtain the optimal layout of WEC arrays, Ruiz et al. (2017) introduced a four-parameter layout description and compared three optimization algorithms of covariance matrix adaptation evolution strategy (CMA-ES) (Hansen and Ostermeier, 1996), a GA (Holland, 1992), and the glowworm swarm optimization (GSO) (Krishnan and Ghose, 2006) algorithm. Their research revealed that, while the GA and GSO performed slightly better (GA outperformed both CMA-ES and GSO by 1%, and 2%, respectively), the CMA was noticeably less computationally demanding (Ruiz et al., 2017). Moreover, Raju (Vatchavayi, 2019) used the derivative-free continuous optimization method, CMA-ES, Bi-level, and alternative to optimize the converters' placement in terms of minimizing their negative interactions and the Nelder–Mead (NM) search algorithm to find the optimal PTO parameters for each WEC. From Ruiz et al. (2017), the best-performed method is a bi-level optimization strategy that is better than alternating one at 9%.

In order to maximize the total absorbed power output of the WECs, Abraham and Kerrigan (2012) formulated an optimal control method for a PTO mechanism that includes linear dampers and active control elements. The solution used was a bang–bang type. Based on the results, the gradient projection method was inexpensive and more feasible than a general nonlinear program (NLP) solver.

A shallow artificial neural network (ANN) was presented by Thomas et al. (2018) to determine optimal latching times in irregular wave conditions. Based on the simulation, for some sea states, the learnable WEC absorbs more than 30% power compared to the best constant latching time in the test wave and absorbs a double amount of the power of the WEC without latching. Furthermore, the latching–declutching optimization is a sophisticated PTO control technique in order to improve the performance of the whole system. Since the cost function in this optimization problem is discontinuous, Feng and Kerrigan (2015) decided to apply a novel derivative-free coordinate-search algorithm, using a formulation based on the past wave information and prediction of the future wave. The algorithm was compared with a derivative-free global meta-heuristic method, the simulated annealing algorithm (SA) (Kirkpatrick et al., 1983), to prove the efficiency.

2.2.1. Bio-inspired algorithms

Bio-inspired algorithms solve challenging problems by mimicking and employing simple nature-inspired optimization mechanisms. This approach mimics nature's strategy, as many biological processes can be viewed as constrained optimization

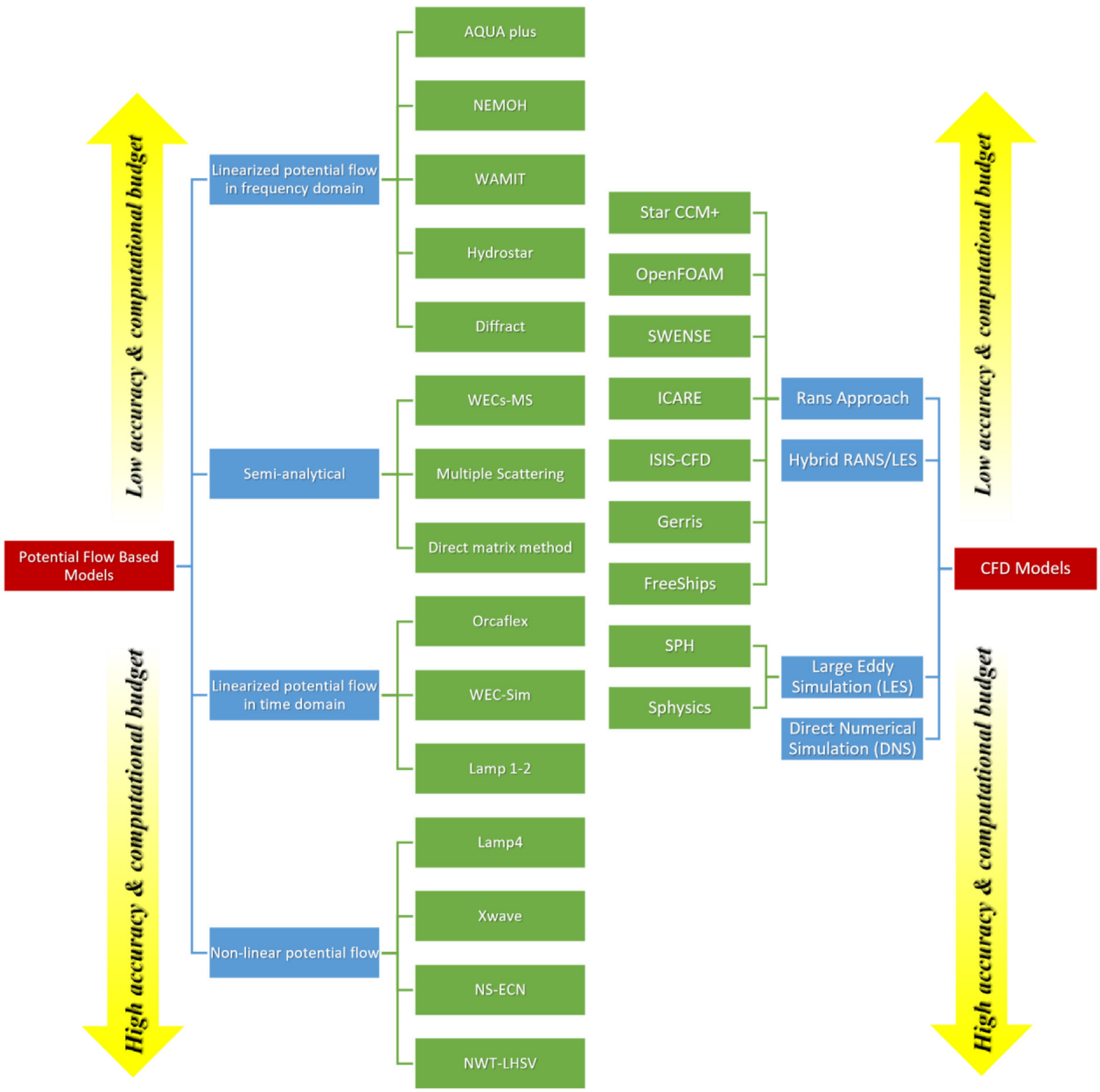


Fig. 7. Classification of common-used numerical approaches and related solvers in wave energy converter modeling, and green boxes reveals the numerical solvers. There are more solvers from each approach that is not mentioned above in this figure.. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

processes. They employ a large number of arbitrary decision-making mechanisms, so they are classified as a subset of randomized (stochastic) algorithms. This approach's popularity stems from the fact that it is helpful for solving a wide range of problems and can be applied to challenging problems in all key areas of computer science (Binitha et al., 2012). Bio-inspired algorithms have been classified into evolutionary-based algorithms (EA), swarm-based intelligence algorithms, and physics-based algorithms, (Fan et al., 2020). Here we discuss two of these classes: the most predominant classes amongst others—Evolutionary Algorithms and Swarm-based Algorithms, inspired by the natural evolution and collective behavior in animals, respectively (Binitha et al., 2012).

Various modern investigations of synergy optimization methods have been recently carried out on the developments of layout, PTO, and geometry parameters on WEC performance, including numerical, genetic, evolutionary, swarm intelligence, and customized local search algorithms. These investigations are summarized in Table 4.

2.2.2. Evolutionary-based algorithms

As a subclass of Bio-inspired Algorithms, Evolutionary Algorithms (EAs) are efficient heuristic search methods based on Darwinian evolution with remarkable resilience and flexibility features for capturing global solutions to complex optimization problems. When using EAs, the likelihood of identifying a near-optimal solution at an early point of the optimization process is relatively high (Galván et al., 2003). The typical procedure of such algorithms is including three steps. In the beginning, they initialized the samples, and then the objective function is calculated with the selecting operation between the former and new ones and use termination criteria for reducing the computation after transforming selected samples to additional ones.

To overview using evolutionary algorithms in the subject of wave energy converter, we start with an early optimization study (Child and Venugopal, 2010a). Parabolic Intersection (PI) and GA methods are used to find optimal array configurations in early WEC optimization studies. Despite the fact that GA outperformed the PI in terms of performance, the PI was

Table 3
Numerical modeling of wave energy converters array in recent articles.

Author	Year	Type of converter	Numerical model	Solver	Reference
Sharp	2017	Point absorber	linearized PF	WAMIT	Sharp et al. (2017)
Wu	2016	Point absorber	Semi-analytical	Multipole expansion	Wu et al. (2016)
Lyo	2019	Point absorber	Linearized PF	NEMOH	Lyu et al. (2019)
Hamed Behzad	2019	OSWEC	Linearized PF	ANSYS AQWA	Behzad and Sanaei (2019)
Ruiz	2017	Point absorber	Linearized PF Semi-analytical	Nemoh, Direct Matrix Method	Ruiz et al. (2017)
Rosenberg	2019	Point absorber	PF time-domain, RANS	Orcaflex, Star CCM+	Rosenberg et al. (2019)
Parker Field	2013	Oscillating cylinder	RANS approach	Star CCM+	Field (2013)
Giassi	2018	Point absorber	Semi-analytical	Fast Multiple Scattering	Giassi and Göteman (2018)
Finnegan	2021	Point absorber	CFD	ANSYS CFX	Finnegan et al. (2021)
Giassi	2020	Point absorber	Semi-analytical, Linearized PF	Multiple Scattering, WAMIT	Giassi et al. (2020b)
Bozzi	2017	Point absorber	Linearized PF time and frequency domain	ANSYS AQWA, hydrodynamic electromagnetic	Bozzi et al. (2017)
Sharp	2018	OWC	Linearized PF	WAMIT	Sharp and DuPont (2018)
Moarefdoost	2017	Point absorber	Linearized PF-Semi-analytical	WAMIT, point absorber approximation	Moarefdoost et al. (2017)
Yang	2020	Point absorber	PF	DNV GL SESAM	Yang et al. (2020)
Amini	2020	Point absorber	Semi-analytical	WEC-MS	Amini et al. (2020)
Neshat	2018,2019	Point absorber	Semi-Analytical	WEC-MS	Neshat et al. (2018, 2020b,c)
Liu	2020	OWSC	SPH	DualSPHysics	Liu et al. (2020b)
Wang	2020	Point absorber	PF	Calculation method	Wang et al. (2020)
engström	2020	Point absorber	Linearized PF	WAMIT	Engström et al. (2020)
Göteman	2018	Point absorber	Semi-analytical	WAMIT	Göteman et al. (2018)
Tay	2017	OWSC	Linearized PF, Semi-analytical	WAMIT, HOBEM	Tay and Venugopal (2017)
Göteman	2017	Point absorber	Linearized PF, Semi-analytical	WAMIT	Göteman (2017)
Ma	2020	Oscillating float	Linearized PF	ANSYS AQWA	Ma et al. (2020)
Balitsky	2014	Point absorber	Linearized PF	WAMIT	Balitsky et al. (2014)
Bharat	2018	Point absorber	RANS, Linearized PF	Star CCM+	Bharath (2018)
Devolder	2018	Point absorber	RANS, Linearized PF	OpenFoam, WAMIT	Devolder et al. (2018)
Faraggiana	2019	Point absorber	PF	Nemoh, WEC-Sim	Faraggiana et al. (2019)
Monroy	2011	–	RANSE	SWENSE	Monroy et al. (2010)

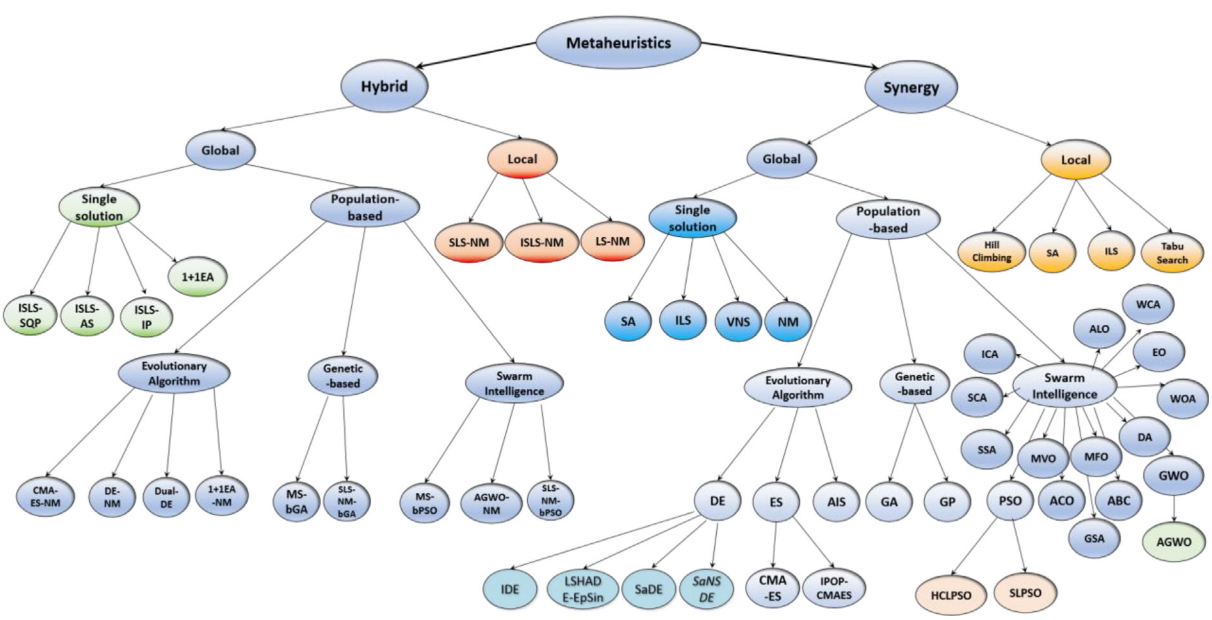


Fig. 8. A comprehensive classified landscape of meta-heuristic optimization algorithms applied in optimizing wave energy converters.

much more computationally efficient. Similar research is done by Moarefdoost et al. (2017) that proposed a heuristic optimization algorithm to find a layout with maximum q-factor. The results of this algorithm outperformed the modified GA. Related research projects by GA can be seen in the below-arguing papers.

Lyu et al. (2019) used GA to optimize both dimensions of individual WECs and the array layout of the WECs' cylindrical buoys. A hidden genes GA (HGGA) is suggested by Abdelkhalik and Darani (2018) for the nonlinear control of the WECs and to optimize system nonlinearities caused by shape, large buoy motions, and

Table 4
Synergy optimization methods: genetic, evolutionary, swarm, heuristic and local search.

Method	Description	Advantage	Disadvantage	Objective	WECs No.
R-S (Neshat et al., 2018, 2020a)	Random Search	Simplicity, flexibility, appropriate for a wide range of applications, easy to get out of local minima	not guarantee optimal solutions, easy to fall into non-optimal areas, semi-blind search, high computational time, low efficiency	Layout	4,16
PE (Neshat et al., 2018, 2020a)	Partial Evaluation	Able to save evaluation time by evaluating population's fitness only partially, speedy evolution at early generations for smaller population size with a lower number of frequencies sampled	requiring high computational time for post-processing, especially for large population size with a higher number of frequencies, low efficiency, less informed and more noisy fitness evaluations, premature convergence, dependence on population size and the number of frequencies sampled	Layout	4,16
1+1EA (Neshat et al., 2018, 2019b, 2020b,a)	Evolutionary algorithm	simplicity, fast search speed, applicable for a wide range of problems	not guarantee the optimal solution, all-at-once buoy placement, stagnation, semi-blind search	Layout& PTO	4,16,49,100
(μ +λ) EA (Neshat et al., 2019a)	Evolutionary algorithm	simplicity, fast search speed, applicable for a wide range of problems	not guarantee the optimal solution, all-at-once buoy placement, stagnation, semi-blind search	Layout	4,16
NM-M (Neshat et al., 2019b, 2020c)	Nelder–Mead simplex direct search + Mutation	Good exploration, low computation	Easy to fall into local optimum and poor handling of discrete optimization problems	Layout, PTO, Geometry	16
DLS (Neshat et al., 2020b)	Discrete Local Search	Fast convergence, high efficiency (farm output), avoiding infeasible layouts and reducing overall search space, strong exploitation ability, high efficiency in large-scale optimization problems	Premature convergence, depends on the resolution of discretization	Layout	49,100
IPM (Neshat et al., 2020a; Dikin, 1967)	Interior Point Method	Fast convergence speed, high efficiency, low computational cost, high scalability, flexible, independent from the number of decision variables or parameters, requires less storage	Less efficient than SQP and AS in some problems	Layout	4,16
SQP (Neshat et al., 2020a; Kraft, 1994)	Sequential Quadratic Programming Search	Robust, high efficiency, flexible	High computational cost, dependence on the number of constraints	Layout, PTO	4,16
ASM (Neshat et al., 2020a; Kanzow, 1996)	Active Set Method	high efficiency, fast convergence speed	High computational cost, low scalability, dependence on the number of constraints, requires large storage	Layout	4,16
SLS (Neshat et al., 2020a)	Smart iterative local search +Smart Mutation	Fast convergence speed, high efficiency, smart local search and initial sampling that results in better exploitation, inexpensive sampled landscape, high efficiency	Greedy selection of buoy placements, dependence on initial placement, difficult to place next buoys after hitting the top boundary of the farm due to occlusion from the front row of buoys for subsequent buoy placement	Layout	4,16

(*continued on next page*)

the PTO. Results showed that the shape-based approach used in this paper has performed 132% better than other methods with a reasonable rate of reaching convergency and can include all the wave data for optimizing the process.

Giassi and Göteman introduced a tool according to GA, for optimizing some of the principal parameters such as the value of draft and radius of a single point-absorber and an array of 4 and 5 WECs, and the optimization results indicate an improvement of the output between 3% and 7%, respectively (Giassi and Göteman, 2017). They extended the GA tool to optimize arrays of 4 to 14 similar point-absorber WECs and obtained 20% increase in the total power output on average in all sizes of the farm (Giassi and

Table 4 (*continued*).

Method	Description	Advantage	Disadvantage	Objective	WECs No.
ISLS (Neshat et al., 2020a)	Improved Smart Local Search	Fast convergence speed, low computation, high efficiency, strong search ability	Greedy selection of buoy placements, dependence on placement history of buoys, poor local search ability, difficult to search for the placement of subsequent buoys, dependence on users to choose the extent of the search sector (angular or radial), all-at-once buoy placement	Layout	4,16
CMA-ES (Neshat et al., 2018, 2019b,a, 2020b,c,a; Hansen, 2006)	Covariance matrix adaptation evolution strategy	Simple, self-adaptive, strong global search ability, few parameters, high performance in optimizing high-dimensional or more challenging problems, continuous and non-separable landscapes, the ability to outshine other standard EAs and global searches, high convergence speed	dependence on objective function, low efficiency in low-dimensional or discrete search space, all-at-once buoy placement, high computational time, premature convergence	Layout, PTO, Geometry	4,16,49,100
DE (Neshat et al., 2018, 2019b,a, 2020b,c,a; Storn and Price, 1997)	Differential evolution	Simplicity, strong global search ability, the ability to solve complex optimization problems, fast convergence speed, the ability to outperform other competitive EAs, few parameters, robust, applicable to high-dimensional complex optimization problems, low computational time	not guarantee the optimal solution, all-at-once buoy placement, poor and unstable convergence and stagnation at sub-optimal points	Layout, PTO, Geometry	4,16,49,100
IDE (Neshat et al., 2020b,a)	Improved Differential Evolution	Strong global search ability, discrete problems, able to outperform other EAs, self-adaptive, fast convergence, high precision	not guarantee the optimal solution, all-at-once buoy placement, easy to fall into sub-optimal locations, low efficiency, especially in discrete optimization problems	Layout	4,16,49,100
GA, bGA (Neshat et al., 2020b,a; Esmaeilzadeh and Alam, 2019; Child and Venugopal, 2010a)	Genetic Algorithm, and binary versions	Simplicity, able to be performed well in a wide range of applications, fast convergence, effective in converging to optimal solutions while considering continuous and discrete factors, avoiding infeasible layouts and reducing overall search space	Dependence on initial population, premature convergence, low efficiency	Layout, geometry, PTO	4,16,49,100
bDE (Neshat et al., 2020b)	Improved binary Differential Evolution	Fast convergence speed, low computational time, strong local search, capable of escaping from local optima, applicable to a wide range of binary optimization problems in different fields, strong exploration, and exploitation, avoiding infeasible layouts and reducing overall search space	Dependence on initial population, premature convergence, low efficiency	Layout	49,100

Göteman, 2018). Following this, Giassi et al. (2017) developed and used the method for arrays of non-homogeneous WECs to obtain optimal wave power parks and reported that GA tool could propose a layout that produce 7% more power than the average layouts.

Sharp and DuPont (2018) presented a GA approach with an additional objective function (a coefficient of cost and power), and studied the spacing effects and minimized the destructive interactions in order to maximize power. The GA (Sharp and DuPont, 2018) with new objective function compared with Parabolic Intersection (PI) and MATLAB'S Genetic Algorithm (Child and Venugopal, 2010b) and outperformed both of them at 2.3% and 2.5%, respectively. The beneficial use of machine learning approaches is introduced by Liu. In Liu et al. (2020b), the study of OWSC started with nine random design parameters, which were simulated by DualSPHysics software. Then, after the capture factors were obtained from training radial basis function neural network (RBFNN), these parameters were optimized by GA. However, there is still a gap in doing research with multi-directional waves combining different positive points of mentioned papers; However, RBFNN prediction accuracy was not competitive (83.33%).

Although interests in utilizing GA are high, other optimization methods have been studied and absorbed by a considerable number of researchers in the last decade. For instance, Wu et al. (2016) employed two EAs of (1+1)-EA and CMA-ES for optimizing a three-tether submerged buoy array. The combination of the aforementioned algorithms proved to be worthwhile, including 1+1EA and CMA-ES. The experimental optimization results for 25 and 50 WECs show that the proposed configurations by 1+1EA produced 3.3% more power than those of CMA-ES. However, the applied wave model in the Wu et al. study was not advanced and near to the realistic sea wave. Fang et al. (2018a) introduced the concept of an adaptive mutation operator to modify the DE algorithm for layout optimization of the three different layouts of point-absorber WECs under a regular wave.

The modified DE algorithm turned out to be more functional (both in calculation convergence speed and achieving a better optimal result) than the traditional DE algorithm with a constant mutation operator; however, the adaptive DE was not compared with the popular and modern adaptive, and self-adaptive DE such as SaDE (Qin and Suganthan, 2005), JADE (Zhang and Sanderson, 2009), EPSDE (Mallipeddi et al., 2011) or novel metaheuristics such as CQFFA (Gharehchopogh et al., 2022), DMDE (Nadimi-Shahraki and Zamani, 2022), GGWO (Nadimi-Shahraki et al., 2022), etc. Bonovas and Anagnostopoulos (2020) optimized construction parameters by EAs (integrated into EASY software) with the total investment cost and the reservoir flow rate as the objective functions. The study (Bonovas and Anagnostopoulos, 2020) demonstrated 30% power enhancement more than the initial configuration using the proposed method.

An efficient analytical wake model with high accuracy and an energy output model for the OWSCs is introduced by Liu et al. (2021). Using the proposed models and DE algorithm for OWSC layouts optimization showed that the staggered layouts were economical and appropriate to maximize the total energy power outputs. However, Liu et al. (2021) do not discuss the application of the advanced mutation and crossover operators in the studied DE. In one of the initial studies, Michael J.D. Powell invented constrained optimization by linear approximation (COBYLA), a numerical optimization method for constrained problems where the derivative of the objective function is unknown (Powell, 1994). Gomes et al. (2012) optimized the dimensions of the floater and tube of an OWC to achieve the maximum wave energy extraction. The algorithms used in this geometry optimization were DE and COBYLA. Based on their study, the relatively large variations in the turbine's damping coefficient had a minor influence on the annual average power. In another relevant study, e Silva et al. (2016) proposed two optimization algorithms that do not require the function gradient, GA and COBYLA, to solve a typical multi-dimensional, single-objective problem. This hydrodynamic optimization method consisted of the main core and also an internal method integrated inside the main one. The principal framework optimized the floater geometry using GA and COBYLA. Sequentially COBYLA algorithm was used in the internal optimization problem to optimize the turbine characteristics and mass distribution. The COBYLA could find an optimal configuration with 5.9 times produced power higher than the predefined geometry parameters.

In Sergiienko et al. (2020), the authors optimized the design of a multi-mode wave energy converter. The objectives were to maximize the power output and minimize the levelised energy cost of a WEC located in the Albany test site in Western Australia regarding unidirectional irregular waves. The design parameters were the radius and the height of the buoy, tether inclination angles, and control variables. To optimize the WEC, the authors applied six different standard meta-heuristic approaches and DE and SaDE (Qin et al., 2008) steadily made advances and finally performed best.

2.2.3. Swarm-based intelligence

As another subclass of Bio-inspired Algorithms, Swarm intelligence (SI) algorithms are valuable because of their flexibility in various problems and ability of strong global search. One of the well-known algorithms is particle swarm optimization (PSO) (Kennedy and Eberhart, 1995). Some of the research projects involving SI mention briefly as follows.

The GA, PSO, and Hybrid Genetic PSO (HG-PSO) algorithms were used to investigate the main WEC parameters' values optimization, and the latter one turned out to be the most proper algorithm (Capillo et al., 2018). Faraggiana et al. (2019) compared the evolution of the minimum LCOE of WaveSub WECs using a GA and a PSO. The results showed that both algorithms operated almost equivalent. See et al. (2012) introduced the application of bio-inspired Ant Colony Optimization (ACO) metaheuristic to optimize the electric PTO for point absorber WECs based on the instantaneous changes in the wave pattern. This led to a notable decrease in the computational time, which is valuable as it allows the WEC to achieve resonance in heave (oscillation) with ocean waves and a marginal deviation at 3.28%.

Although a wide range of genetic, evolutionary and swarm intelligence algorithms have been applied to optimize different components of the wave energy converters, there is not a straightforward way to select the best optimization method. A performance comparison between Evolutionary and Swarm optimization algorithms can be seen in Table 5.

2.3. Local search methods

Local search metaheuristics find good solutions by making small changes to a single solution iteratively. Hence adjacent solutions are relatively close to each other. By applying a single move to a given answer, a set of new candidate solutions can be achieved. A solution from the neighborhood replaces the current solution in each iteration (Sörensen and Glover, 2013).

A stochastic optimization approach was applied by Tedeschi et al. (2013) to optimize energy storage system sizing to reduce the final cost of energy. The simulation results of Jusoh et al. (2021) reveal that the average electrical power produced from the hydraulic power take-off (HPTO)units optimized by the non-evolutionary Non-Linear Programming by Quadratic Lagrangian (NLPQL) and GA raised to 96% and 97%, respectively, in regular wave conditions. Since the NLPQL is a local search method, it is much faster but less reliable than GA. In WECs with a data-driven linear generator configuration type, the Halbach linear generator is used in the secondary structure to minimize energy loss. To increase this generator's efficiency, the SA was used by Liu et al. (2020a).

2.4. Hybrid optimization methods

Many algorithms combine ideas from different classes, which are called hybrid methods (Sörensen and Glover, 2013). Researchers have also conducted comparative studies to evaluate optimization methods' performance. Such studies can be highly beneficial in assisting end-users in selecting the best optimization method for their problems (Beiranvand et al., 2017). A wide variety of metaheuristics (Neshat et al., 2018) was proposed and compared for the layout optimization of multiple fully submerged three-tether buoys. The model used by the authors was an artificial wave scenario including seven wave directions and 50 wave frequencies. The problem was arranging buoys to increase the constructive interactions between them and decrease the destructive ones to maximize the power output. It was found that a combination of a novel heuristic and Nelder–Mead search (LSNM) outshined other optimization methods in terms of maximum power output for both 4- and 16-buoy configurations. Moreover, analyzing the results from a random search, partial evaluation, CMA-ES with different settings, DE, iterative local search, and local sampling together with NM showed that there is only a considerable difference (around 20%) in the mean output of the mentioned methods. In the following, in Neshat et al. (2019b), a practical and efficient hybrid heuristic was introduced, combining a symmetric local search and Nelder–Mead simplex direct search with a back-tracking optimization strategy (SLS-NM-B) to optimize both layout and PTO parameters of WECs. The back-tracking algorithm tries to improve the location of the converters with the lowest absorbed power. Once these converters have

Table 5
A comparison between Evolutionary algorithms and Swarm intelligence methods.

#	Evolutionary algorithms	Swarm intelligence algorithms
1	Moderate convergence speed in unimodal functions	Fast convergence speed in unimodal search space (PSO performed better than DE Vesterstrom and Thomsen, 2004)
2	Strong global search ability	occasionally stagnates at a local optimum
3	Considerable performance in noisy problems	Strong exploitation ability with high precision
4	Competitive achievements in the highly multimodal functions	More sensitive to the control parameter initialization
5	More robust and reliable	Self-organization is strong and inherently parallelism and distributed features. (Bansal et al., 2019)

been selected, a stochastic local search is employed to analyze the neighborhood spot of the converters by some feasible samples. In order to develop a local search effectively, the radius search is fixed at 50 m initially and will be reduced to 5 m. A pool of feasible locations which are evaluated is made to find the best spot with the highest power output. This process is iterated for N number of poorly located converters. Fig. 10 shows the technical search pattern of SLS-NM using a local random sampling for placing WEC one by one and adjusting the positions in order to maximize the mean power output of the whole wave farm. It can be seen that after reaching the boundary of the farm, finding an optimal place for the remained WECs is challenging due to a complex interaction between WECs and wave directions. Both SQP and Active-set numerical search algorithms mostly focused on the upper and lower area's bounds, and they followed a straight search direction. However, Interior point and Nelder–mead developed a local search in different directions The results showed that the (SLS-NM-B) was able to outperform other meta-heuristics in terms of total maximum power output. The authors used two real wave scenarios with 4- and 16-buoy farms compared to the previous works.

In a similar work, Neshat et al. (2019a) proposed an adaptive neuro-surrogate optimization (ANSO-S-B) algorithm to maximize the total power of a wave farm by optimizing the WEC array. The proposed method was a mixture of a surrogate Recurrent Neural Network (RNN) model, a grey wolf optimizer (GWO), a novel symmetric local search, and a back-tracking strategy to further arrangement of buoy placements. ANSO-S4-B performs better in three of four tested sea sites between the tested algorithms. Furthermore, the proposed algorithm performed better in layout optimization than local search plus Nelder–Mead (LS-NM) by 3.6%. The proposed methods were applied to four real wave scenarios from the coasts of Australia consisting of 4 and 16 converters.

After that, the study continues in Neshat et al. (2020a) where the buoy positions were surveyed through a new hybrid method that combines a local search method with a numerical optimization method. Methods in two groups of population-based and single solution optimizers were used to compare the performance of the proposed hybrid method, which utilized a knowledge-based surrogate power model. The most effective method to gain more power output was a smart local search with or without NM. The improved smart local search combined with NM, sequential dynamic programming, interior point search, and active set search. The last one performs the best among all of the optimization methods. The author mentions the absence of backtracking optimization, and this concern is solved in the following two papers. In Neshat et al. (2020c), a novel hybrid Cooperative Co-evolution algorithm (HCCA) was introduced to optimize wave farm power output by considering the positioning and PTO parameters for each WEC. This algorithm includes three methods: social learning particle swarm optimization (SLPSO) (Cheng and Jin, 2015), self-adaptive differential evolution with neighborhood search (SaNSDE) (Yang et al., 2008), and a new adaptive grey wolf optimizer (AGWO), with the same population to solve the problem cooperatively and benefit from a backtracking optimization algorithm. Note that HCCA responds better than other algorithms in terms of the convergence speed and the WEC layout quality; however, in the 4-buoy layout, it is not the only best answer.

Recently, in another successful application of cooperative co-evolutionary algorithms, Neshat et al. (2022) developed a new multi-swarm cooperative co-evolution algorithm to optimize the placement of offshore WECs. The proposed method consisted of three swarm intelligence-based methods, including the multi-verse optimizer (MVO) (Mirjalili et al., 2016), the equilibrium optimization (EO) (Faramarzi et al., 2020), and the moth flame optimization (MFO) (Mirjalili, 2015) with a backtracking strategy. They applied the proposed algorithm alongside fourteen optimization methods to the real wave sites on Australia's coasts, including Perth, Adelaide, Sydney, Tasmania, Brisbane, and Darwin, with four and nine WECs. The proposed method proved to be faster and more efficient than other optimization algorithms.

In Neshat et al. (2020d), the authors developed a bi-level optimization framework for tuning the three different types of design parameters of a multi-mode WEC simultaneously in order to reduce the levelised cost of energy (LCoE) and maximize mean power output. The design parameters included the geometry, tether angles, and power-take-off (PTO) parameters. The optimization approach consisted of a self-adaptive differential evolution method applied at the upper level and a local downhill search method at the lower level. The results showed that the proposed method outperformed other algorithms in terms of convergence speed, absorbed power, and levelised cost of energy.

As the runtime of WEC array evaluation exponentially increases by raising the number of converters, developing a fast and effective optimizer for large wave farm is substantial. In order to handle this challenge, a hybrid multi-strategy evolutionary algorithm was proposed (Neshat et al., 2020b) to maximize the power output of a large-scale farm of up to 100 WECs by optimizing the WEC arrays. The proposed method was a combination of a smart initialization, a binary population-based evolutionary algorithm, a discrete local search, and continuous global optimization. The results showed that the proposed methods could outperform other optimization algorithms on two real wave scenarios and conquer the difficulties of the large wave farm optimization, such as significant interactions between the WECs and a large number of dimensions of search space.

Hybrid meta-heuristic methods for optimizing different characteristics of wave energy systems are summarized in Tables 6 and 7. It can be seen that in the majority of the proposed methods, a combination of a global search and local search performed better than other types of hybridization. However, the hybrid heuristics that include local tracking with modifications like surrogate

Table 6
Overview of the hybrid meta-heuristic methods application (Part1) to optimize the layout, PTO and geometry parameters of wave energy converters.

Method	Description	Advantage	Disadvantage	Objective	WECs No.
LS-NM (Neshat et al., 2018, 2019a,b, 2020c,a)	Repeated local sampling for buoy positions + Nelder–Mead Search for PTO parameters of the last buoy	Strong exploitation, low computation, fast convergence, high efficiency	Greedy placement of the WEC, slow optimization speed for later buoy placements	Lay-out&PTO	4,16,49,100
LS+NMallDims (Neshat et al., 2018, 2020a)	Local sampling + using Nelder–Mead search for all dimensions	Strong local search ability, and more robust than LS-NM	Greedy selection of WEC placement, slower than LS-NM, large computation	Layout	4,16
NM-Norm2D, NM-Unif2D (Neshat et al., 2018, 2020a)	Nelder–Mead search + Normal distribution/Uniform distribution	Strong local search ability, low computation, and fast convergence	Greedy placement of WECs, premature convergence, and termination	Layout	4,16
SLS+NM(2D) (Neshat et al., 2019b, 2020c)	Symmetric Local Search for buoy positions + Nelder–Mead for PTO	Strong neighborhood searchability, high efficiency, fast convergence rate, smart initialization, better exploitation of constructive interactions between buoys, outperforms other EAs for some wave models, very fast and efficient in less challenging problems, cheap sample landscape	Dependence on its starting point (the placement of the first buoy), low efficiency in complex wave model, like Sydney wave scenario, greedy selection of layout positions	Lay-out&PTO	4,16
SLS-NM-B (Neshat et al., 2019b, 2020c)	Symmetric Local Search for buoy positions + Nelder–Mead for both PTO and new buoy positions + Backtracking to refine the previous buoy positions	Strong local search ability, speedy search, low computational cost, high efficiency for small size of farm, outperform other methods in terms of convergence speed and power production	Poor performance in optimizing PTO parameters, high dependency to the first WEC's location	lay-out&PTO	4,16
ANSO-S (Neshat et al., 2019a)	Adaptive Neuro-Surrogate optimization method SLS+GWO	High efficiency, high convergence rate, trained the model fast and efficiently, low computational cost, accurate and easily scalable to larger farm sizes, self-adaptive, needs no pre-processing, ability to collect the required training data in real-time during the sampling and optimization of previous buoy positions, adaptive hyper-parameter tuning, capable of exploiting constructive interactions between buoys	initial greedy placements, ineffective WEC's placement once the farm boundary is reached, lack of adaptive training for the WEC's placement once the farm boundary is reached, lack of a mechanism for repairing the WEC's location	Layout	4,16
ANSO-S-B (Neshat et al., 2019a)	ANSO + Backtracking (SLS+GWO+BO)	Able to revisit the placement of previous buoys, high power output, fast search speed and convergence, fast online training, adaptive mutation rate based on the amount of power absorbed by buoys, low computational time, self-adaptive, able to save the run-time for evaluating samples, adaptive hyper-parameter tuning, the surrogate training time	Lack of adaptive training for the placement of buoys once the farm boundary has been reached, increase the computational cost for large-scale wave farm	Layout	4,16
SLSNM-bGA (Neshat et al., 2020b)	SLS-NM + binary GA + Rotate	Fast convergence, high efficiency for large-scale wave farm, low computational time, smart initialization, the ability to avoid premature convergence	lack of a mechanism for repairing the WEC's location, slow convergence speed related to bGA, inefficient rotate strategy, computationally expensive for small-scale (<20) farm	Layout	49,100
SLSNM-bDE (Neshat et al., 2020b)	SLS-NM + binary DE + Rotate	Fast convergence, high efficiency for large-scale wave farm, low computational time, smart initialization, the ability to avoid premature convergence	computationally expensive for small-scale (<20) farm, lack of a mechanism for repairing the WEC's location, inefficient rotate strategy	Layout	49,100
SLSNM-bPSO (Neshat et al., 2020b)	SLS-NM + binary PSO + Rotate	Fast convergence, high efficiency for large-scale wave farm, low computational time, smart initialization	lack of a mechanism for repairing the WEC's location, computationally expensive for small-scale (<20) farm, trapped in a local optimum, and inefficient rotate strategy	Layout	49,100

Table 7
Overview of The hybrid meta-heuristic methods application (Part2) to optimize the layout, PTO and geometry parameters of wave energy converters.

Method	Description	Advantage	Disadvantage	Objective	WECs No.
Multi-strategy algorithms (bGA, bDE, bPSO) (Neshat et al., 2020b)	SLS-NM + bGA/bDE/bPSO-Rotate + DLS + CLS	Fast and effective exploration and exploitation, enhances layout locations by backtracking, high efficiency, especially in Sydney wave scenario and smaller farms, smart initialization, fast convergence speed, effective for large-scale wave farm and discrete searchability, efficient continuous global optimization, robust for complex wave scenarios	Slow search speed and convergence rate, ineffective in low-dimensional optimization problems and dynamic search space.	Layout	49,100
SLS-NM (Neshat et al., 2020a)	Smart Local Search with three samples of the mutation + surrogate power model + Nelder–Mead search	Fast convergence speed, high efficiency in small-scale wave farm, smart local search that results in better exploitation of constructive buoy interactions, inexpensive sampled landscape, smart initial sampling	Initial greedy selection of WEC's placements, easy to fall into local optimum, expensive computation for large-scale wave farm optimization, sub-optimal solutions, dependence on initial placement, difficult to place next buoys after hitting the top boundary of the farm due to occlusion from the front row of buoys for subsequent buoy placement	Layout	4,16
ISLS-NM (Neshat et al., 2020a)	Improved Smart Local Search (10 samples) for the initial sequential buoy placements + Nelder–Mead search	Fast convergence, strong local searchability, effective exploitation of constructive buoy interactions, low computation, high power output and efficiency, and angular and radial extent of the search sector for the wave scenario	Greedy selection of buoy placements, dependence on placement history of buoys, poor local searchability for the placement of subsequent buoys, dependence on users to choose the extent of the search sector (angular or radial), all-at-once buoy placement	Layout	4,16
ISLS(II)-F (Neshat et al., 2020a)	Improved Smart Local Search (for initial sequential Nsb-buoy number) (3 samples)+ Applying SQP + fast placement using a distance as a proxy function	Automatic definition of the search sector, fast search speed due to having a distance-based proxy function, the highest convergence rate compared with other SLS, ISLS, and ISLS(II) methods, high efficiency in most wave scenarios	Placing the WEC in the search space by the best first option, vary in performance between scenarios, inefficient in complex wave environments, such as Sydney, due to have a distance-based proxy, all-at-once buoy placement	Layout	4,16
ISLS(II)-SQP (Neshat et al., 2020a)	Improved Smart Local Search(II) (for initial sequential Nsb-buoy number) 3 samples + Sequential Quadratic Programming Search	Automatic definition of the search sector, able to refine the placement of each buoy by performing SQP method, high efficiency	Greedy selection of buoy placements, high computational time of SQP method, is not able to improve the location of WECs placed in the corner of the wave farm	Layout	4,16
ISLS(II)-AS (Neshat et al., 2020a)	Improved Smart Local Search(II) (for initial sequential Nsb-buoy number) 3 samples + Active-Set Search	Able to refine the placement of each buoy via Active Set search method, strong exploitation and exploration, quick coverage of the search area, high efficiency and maximum layout power, able to outperform other EAs, fast convergence speed, capable of placing all buoys in high-energy locations, one-at-a-time buoy placement	Greedy selection of buoy placements, dependence on how well the first row is aligned with the diagonal of the farm area, absence of backtracking to further optimize buoy positions once they have been placed	Layout	4,16
ISLS(II)-IP (Neshat et al., 2020a)	Improved Smart Local Search(II) (for initial sequential Nsb-buoy number) 3 samples + Interior-Point Search)	Strong constrained search ability, high efficiency, fast convergence	Greedy selection of buoy placements, all-at-once buoy placement	Layout	4,16

power models, backtracking strategies, or sector search were more efficient than other hybrid models in terms of convergence rate.

In order to provide a precise classification overview of the hybrid optimization methods that were applied in improving the performance of WECs, Fig. 9 illustrates a technical diagram of the different hybridization models of local search with evolutionary algorithms, swarm intelligence methods, cooperative co-evolutionary methods, multi-strategy EAs and surrogate optimization methods.

To sum up, it is clear that researchers are substantially moving forward to investigate, develop and apply various optimization algorithms to encounter optimal solutions for WECs. However, proposing the best optimization framework for different

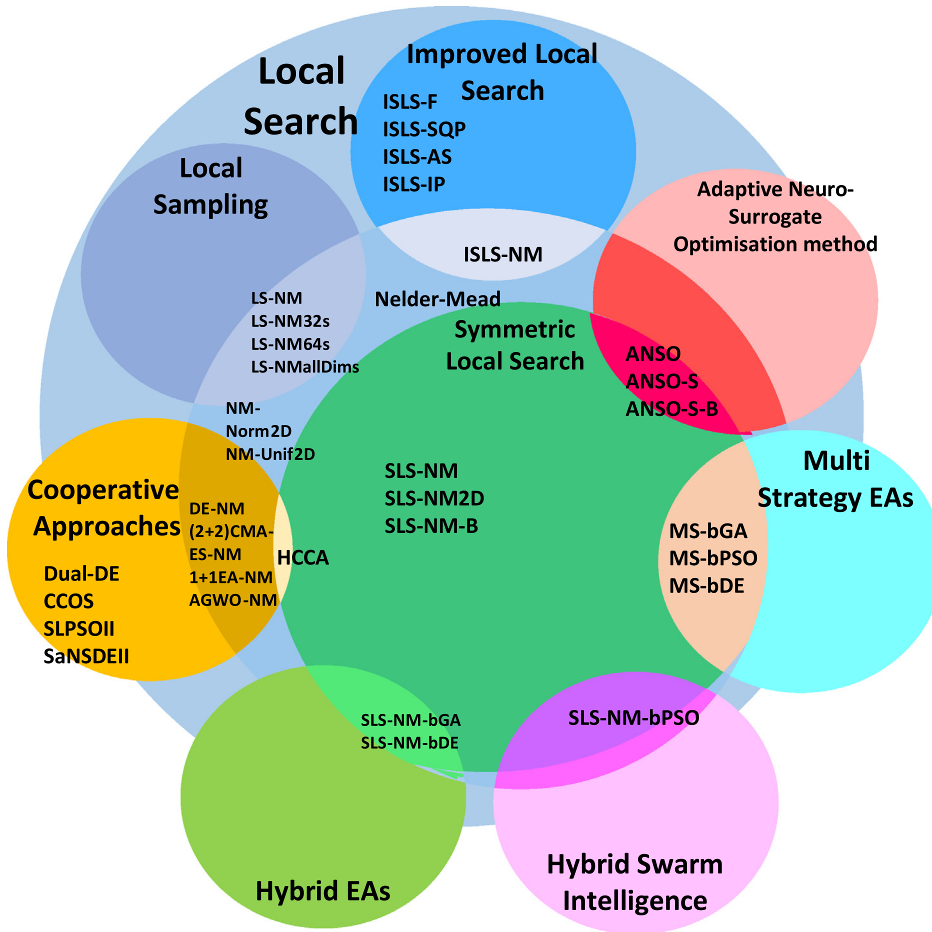


Fig. 9. A technical classification of the applications of wave energy converters optimization algorithms.

components of WECs optimization is still tricky. As a result, the application of ANSO and HCCA are strongly recommended because they give viable solutions in optimization studies, especially the study of layout and PTO. Furthermore, despite the good results, excessive studies on different GA algorithms prevent the academic society from exploring other algorithms. On the other hand, swarm intelligence algorithms were not surveyed thoroughly. Finally, we suggest considering multi-objective functions with the mentioned algorithms. Multi-objective optimization has been applied in many fields of renewable energy engineering, where optimal decisions should be considered in order to achieve a significant trade-off between two or more conflicting objectives. In wave energy optimization, we can consider more than one objective, generally power output maximization, such as minimizing the design and maintenance costs of the converters, finding the optimal cable length for connecting the converters and also minimizing the space of the wave farm. In recent years, several multi-objective swarm intelligence methods have been proposed, such as multi-objective ant lion optimizer (Mirjalili et al., 2017c), multi-objective Salp swarm algorithm (Mirjalili et al., 2017a), multi-objective dragonfly algorithm (Mirjalili, 2016), multi-objective water cycle algorithm (Sadollah et al., 2015), multi-objective grasshopper optimization algorithm (Mirjalili et al., 2018), multi-objective multi-verse optimization (Mirjalili et al., 2017b), multi-objective grey wolf optimizer (Mirjalili et al., 2016), etc.

3. State-of-the-art review

In general, waves are generated from two sources, winds and swells. The wind or sea waves results from local wind condition; however, swell comes from the storms and winds from away fields. Although the definitions of them are quite similar, there are differences such as low steepness in swell waves to avoid breaking in deep seas, and shorter wave frequency of wind waves compared to the swell waves. The combinations of these two waves form the incoming waves and affect the converter's motion considerably. The incoming waves or incident waves impact the first device, then causes a displacement in the device, subsequently, the motion resulting from the device creates the radiated waves. Now there are two waves affecting the second device which is producing its own radiated power; therefore, this chain of waves occurs with the possibility of affecting the former device. Note that the PTO parameters are related to the radiation properties of each device, and by optimizing these parameters, more energy will be extracted. Moreover, after the wave hits a converter, the wave diffracts, and due to this phenomenon, a spectrum is made around the converter representing the amplitude of the wave. This may whether increase or reduce the wave height. Such wave phenomena interact and make a difference in the absorbed power and arrangement of the converters. For example, diffracted and incident waves create the excitation force, and similarly radiated waves have relations to added mass (for simplicity it can be considered as the volume of fluid moving with the buoy) and damping force. As we discussed in 2, selecting an approach to simulate and solve hydrodynamic coefficients, results

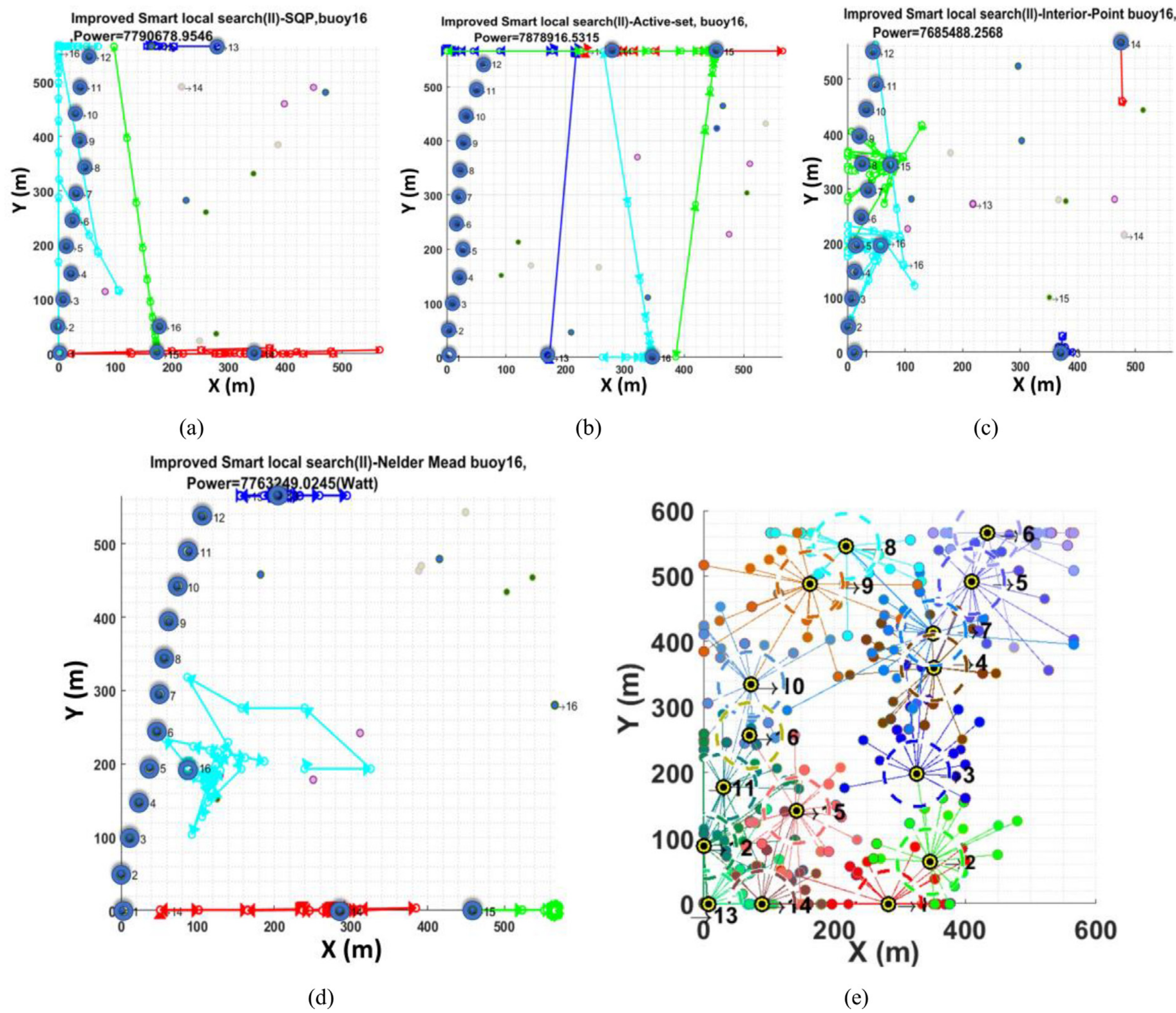


Fig. 10. The performance of ISLS(II) (Neshat et al., 2020a) combined with (a) SQP, (b) Active-set, (c) Interior-Point, and (d) Nelder–mead in optimizing the placement of the 16 WECs based on a simplified irregular wave model from left to right. (e) LS-NM algorithm (Neshat et al., 2019b) based on the Sydney wave model Power = 1.56 MW, q-factor = 0.91), the internal colored circles represent the safety distance.. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

in calculating applied forces on each WEC. When in potential flow solvers, for instance, hydrodynamic coefficients such as added mass, damping coefficients are solved, all forces acting on a WEC device can be calculated. According to the Newton's second law, which is mass of the body multiplied by acceleration is equal to the acting forces, various forces play a part in solving the equation of motion.

These forces are including the excitation force, radiation force, PTO force, damping force, mooring force, hydrostatic restoring force, and viscous force, which can be seen in Fig. 11. Based on the discussion in Penalba et al. (2017b) forces such as Froude–Krylov force, which is introduced by the unsteady pressure field generated by undisturbed waves, and additional force such as drift or wind or other body-water interaction, are also acting on the body. To be more precise, using the nonlinear Froude–Krylov force together with a quadratic viscous model would result in more accurate solutions to hydrodynamic interactions problem in heaving point absorber (Peñalba Retes, 2020).

Furthermore, other nonlinear phenomena are influencing the process of harnessing energy. For instance, sloshing is relative to the enclosed water, or slamming is coming from the impact of device on the surface of water. Therefore, based on the type of converter, relative forces should compute and consider to raise the accuracy. It is clear that some of the discussed forces can be neglected whether the converter is floating or submerged, point absorber, attenuator, or terminator. Then, after calculating the acting forces, the outcome of the interaction on each buoy should be determined.

Subsequently, we focus on three important criteria for optimizing wave energy converters, PTO, layout, and geometry. These subjects are necessary to consider in array modeling to absorb maximum energy.

3.1. Layout configuration

Many research projects studied the possibility of increasing the energy absorption of the array by considering different layouts. Such undesirable layouts may decrease 30% of the array power or an optimal arrangement causes a rise of more than 10% to the total absorbed energy (Child et al., 2011). Throughout the last decade, many papers surveyed both simple regular patterns and random ones. However, optimized patterns may be a reliable choice in order to have constructive effects on extracting power (Neshat et al., 2020c; Moarefdoost et al., 2017; Wu et al., 2016). A formulation proposed for optimizing a layout of WECs position can be designed as follows:

$$Power_{\text{All}} = \operatorname{argmax}_{\mathbf{X},\mathbf{Y}} Power_{C_t}\,(\mathbf{X_i}, \mathbf{Y_i})$$

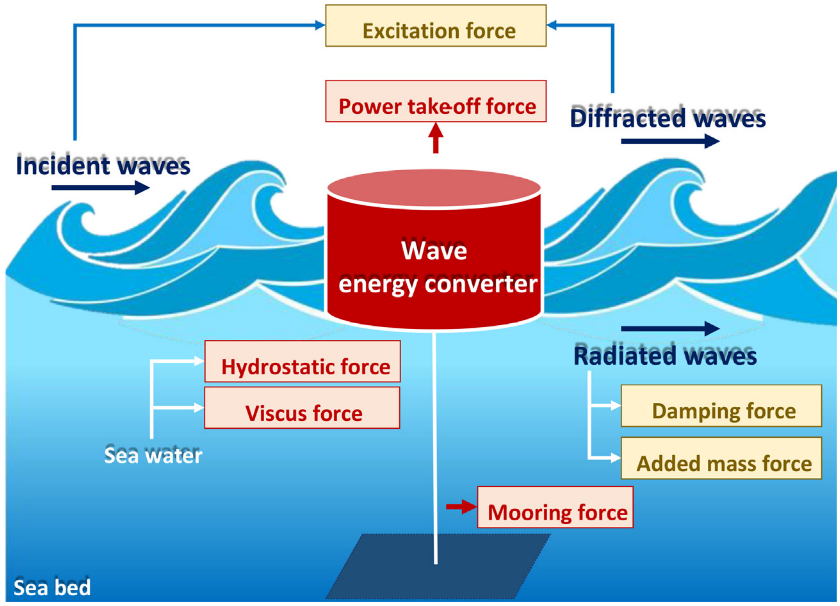


Fig. 11. An illustrative look on the acting forces on a wave energy converter.

Subject to

$$[X_i, Y_i] \in \Phi, i = 1, \dots, N$$
$$\text{dist}\left((X_i, Y_i), (X_j, Y_j)\right) \geq D_s \quad i \neq j = 1, \dots, N$$

where N shows the maximum number of WECs that should be constrained over a bounded area of a wave farm. Φ is a square-shaped form of the wave farm size where the converters are placed at x-positions $X = [x_1, x_2, \dots, x_N]$ and corresponding y positions $Y = [y_1, y_2, \dots, y_N]$. $Power_{C_i}$ is the absorbed power of one WEC using the wave model, and D_s is the minimum distance (safe distance) among converters.

Several factors have effects on the positioning of buoys in the array. They may have a positive or negative impact based on the overall goal of a project. To be more specific, a shorter distance between WECs mostly increases the destructive effects while decreasing the cabling costs. Six of the most important factors investigated in the layout papers are introduced briefly.

1. The number of WECs directly determines the layout configuration. Using more than four converters allows the investigation of polygons and circular layouts.
2. The separation between each converter can alter the array's interaction effects. Suppose the separation increases to a large number (see Fig. 12 (a, c)). In that case, the array's interaction effects could be negligible, and the power absorbed by an array would be equal to the power of isolated powers (De Andrés et al., 2014). However, it can be noted that the optimal distance between two WECs can be various and depends on the wave characteristics (Neshat et al., 2019b). Fig. 12(d) shows that the pick of energy can be obtained at a distance between 50 m and 75 m and the average absorbed power of two converters decreased or flatted by rising the distance.
3. The sea state is critical when it comes to the power absorption parameter. When the system's natural period is close to the wave period, wave interaction effects work productively, and a considerable amount of power is absorbed, According to Babarit (2010). Furthermore, in the case of regular waves, both wave direction and wave frequency directly affect the excitation force, and the excitation force acting on the device has a significant impact on the interaction factor (Tay and Venugopal, 2017).
4. Wave direction can be important in determining layout, and it can be investigated by rotating the array pattern or theoretically using different definitions throughout the study. The majority of papers consider unidirectional direction, whereas Göteman et al. (2018) provide relationships and descriptions for multi-directional waves.
5. The extracted power is affected by the size of each WEC, as discussed in Section 3.3.
6. Finally, considering the interaction between waves and devices is essential when positioning the buoys to avoid destructive effects (Göteman et al., 2014; Sharp et al., 2017).

On two levels, there are various layouts evaluated with the aforementioned aspects in array configurations. First, publications cover regular patterns for arrays such as linear, circular, arrow shape, rectangular or square shape, staggered, random, polygon, hexagonal, and other configurations. Second, the urge to extract as much energy as possible from any pattern condition motivates researchers to use optimization algorithms to determine the best layout for converters.

Göteman et al. (2014) investigated the park layout as the number of converters increased from 4 to 64. According to this study, increasing the number of converters in the park reduces the power of each WEC. Furthermore, a survey of two wave periods with a 1-second difference revealed that the shorter period captures more power output. It should be noted that the configurations were mostly rectangular, with a semi-circular layout being used to compare the results. In the study of Bosma (Bosma et al., 2020), who outlined numerical and physical array testing, optimized and non-optimized layouts with 5 OWCs were considered. The results showed that when the layout is optimized, the average power in regular and irregular waves increased by 12% and 7%, respectively. In the study of Amini et al. (2020) four regular layouts (namely the linear triangular square and pentagon) in four locations in Australia were assessed under different separation and dominant wave directions. The most harnessed energy was in a linear configuration with a separation distance of 165 m. Baltisky (Balitsky et al., 2017) concluded that the separation between WECs should be increased to reduce interactions for a constant wave period. To test the application of a generic coupling methodology, Verbrugghe et al. (2017) tested

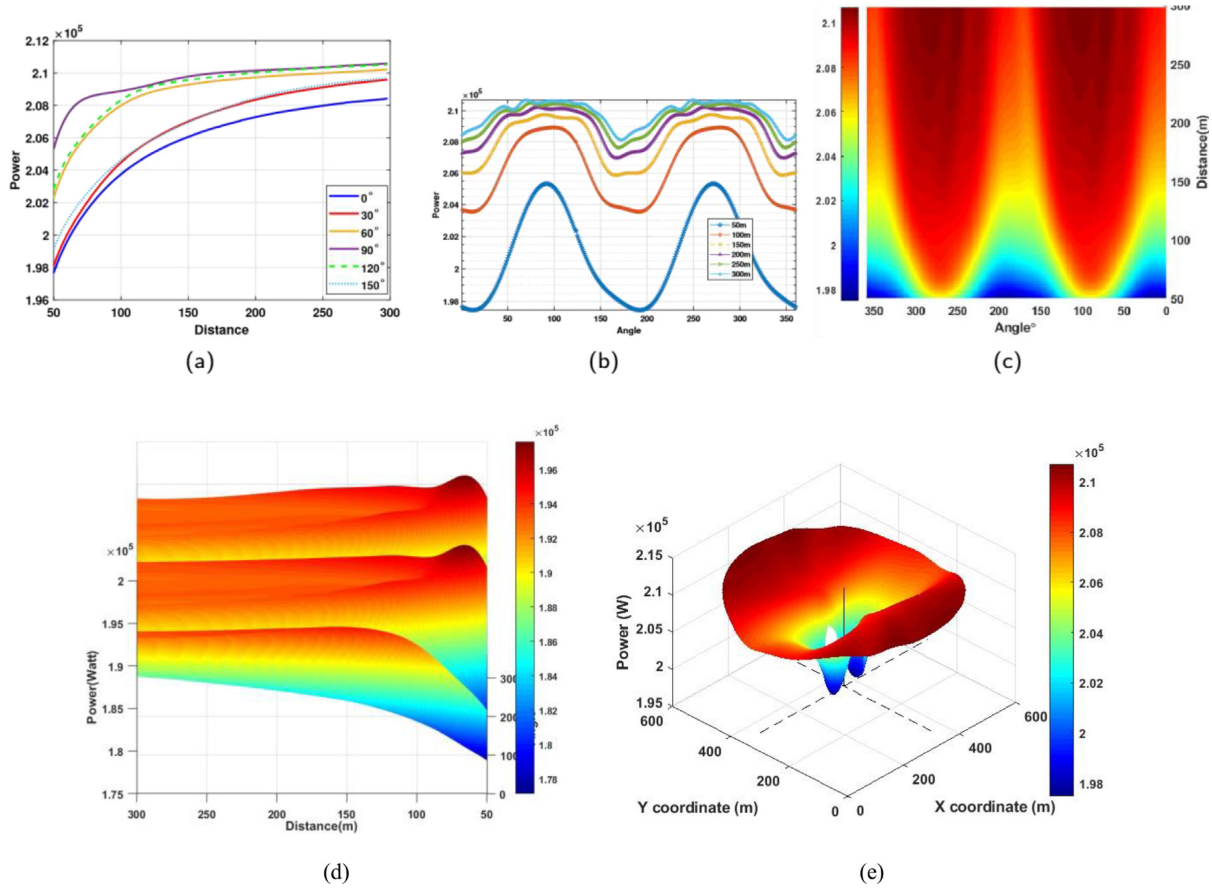


Fig. 12. Analyzing the power output of 2-buoy layout's distances by 360 degrees. It can be seen clearly that increasing the distance between two buoys with different angles causes amplifying the total power output based on the Sydney wave model (Amini et al., 2020; Neshat et al., 2020a). (a) evaluating the distance range from 50 m to 300 m with six various angles for Sydney wave model. (b, c) various intersection angles and distances between two WECs based on the Sydney wave site. (d) A 2D power landscape of the relationship between the distance and the power of two-buoy layout for the Perth wave model. (e) A 3D power landscape of a two-buoy array based on the Sydney wave scenario (Neshat et al., 2020a).

ten programs consisting of one to five WECs in various arrangements, wave depths, and bathymetries. Garcia-Rosa et al. (2015) investigated a control-influenced array layout, which allowed wave farms to absorb more power with 2-3-4 WECs in the linear, triangle, and square configurations. It was demonstrated that array performance could be improved by up to 40%. Raghukumar et al. (2019) investigated the rectangular array layout and separation between WECs to absorb maximum power while minimizing environmental effects. It is concluded that when WECs are placed close to each other, shadowing effects occur, and absorbed power decreases as a result. Giassi et al. (2020a) examined the park layout and concluded that for parks with fewer than 20 converters, converters should be placed perpendicular to the wave direction to reduce cable length. De Andrés et al. (2014) takes into account interactions factor in linear, triangular, and square layouts with WECs ranging from 2 to 4. In this case, it was demonstrated that linear geometry has destructive interaction efficiency, and the other two have similar efficiencies in terms of sea state conditions. Liu et al. (2021) investigated various staggered layouts of OWSC with varying dimensions and optimized them using the DE algorithm. The mean capture factor of an array was discussed in Noad and Porter (2015). The highest efficiency for 3 WECs layouts and 5 WECs layouts was increased by 5 and 7 percent, respectively, compared to a single device's performance. In this study, bowl-like or chevron patterns had the greatest positive increase in power absorption. López-Ruiz et al. (2018a) studied the performance of different configurations during the life cycle of WECs, intending to maximize average extracted energy during that period of time while also minimizing interaction effects between WECs. They found that the arrow layout is the most efficient, absorbing up to 20% more energy than the other geometries.

Moarefdoost et al. (2017) surveyed symmetric and asymmetric layouts and used a heuristic optimization to deduce symmetric layouts answers better except for layouts with four WECs. Using GA in Giassi and Göteman (2017) resulted in a spatial layout with no negative interactions. Furthermore, they believe that this may be unimportant in terms of the number of WECs. Göteman et al. (2015b) used various layouts in their study and concluded that, except for the rectangular configuration, converters placed away from incoming waves capture less power than those placed closer. According to Sharp and DuPont (2018), increasing the number of converters may initially improve array performance, but after a while, additional devices reduce array performance. It is inferred from Sharp and DuPont (2015), evaluating the array with optimum power alone is insufficient; however, using a robust optimization method that includes cost properties in the objective function would result in more reliable outcomes. Their proposed GA gives more flexibility in the number of WECs as well as considering multidirectional waves. Valuable studies have been done by Neshat et al. (2020a, 2019a) to optimize WEC positions for maximum power output. In Neshat et al. (2020a), the 4-buoy layout is mostly aligned and perpendicular to the predominant wave. Likewise, in the 16-buoy layout, the WECs were placed mostly in the feasible area's diagonal. Another publication of Neshat et al. (2019a) optimized the layout with a proposed ANSO algorithm to place the WECs. The optimal layout is derived with the sequential placement of the converters where the starting point of placing them is suggested at the bottom right of the area.

Table 8 congregates some of the recent publications in terms of their configurations, number of WECs, type of

converter, and determinate the criteria for selecting the master layout. In a comparative point of view, the arrangement of WECs must not be parallel to the wave direction in order to escape the shadowing and masking effects. Two of such layouts are linear and arrow which placed perpendicular to the wave direction. As it can be seen in Fig. 13, while the arrow (wedge) layout is one of the superior positioning showed both face up and down in (b) and (c), the superior arrow layout is the one with its first converter facing the incoming waves, placed at the tip of arrow, similarly to shape b. Also linear layout perpendicular to wave direction is important to consider and optimization study of Neshat Neshat et al. (2020a) agrees with this layout which is demonstrated in (a). Furthermore, Fig. 14 demonstrates the landscape of interpolated wave energy based on the best layout found by different optimization algorithms (CMA-ES, DE, LS-NM, and ISLS(II)-AS) for the Perth wave model. We can see how a correct position of a WEC can produce a constructive interaction and reinforces the average total power output of the farm and vice versa.

To sum up, more separation between converters and augmenting the number of WECs increase the absorbed power. However, after a while, it diminishes the mean harnessed energy. Furthermore, a shorter wave period results in more power output. Moreover, the dimensions of a WEC need to satisfy capturing more energy and lower expenditure. Correspondingly, the master configuration is different in each study. Although in Göteman paper (Göteman et al., 2020), layout trends are likely to be aligned and perpendicular to the direction of the predominant wave, it is worth mentioning the wedge (arrow) shape and staggered layouts in regular patterns without using optimization methods to return worthful outputs. Finally, optimization is an alternative choice because it searches for all the possible solutions, so the results become more viable and secure, and an increase in the number of publications about layout optimizations confirms this. It is concluded that a hybrid algorithm combining the local search method and bio-inspired method introduced by Neshat et al. (2020c) outperforms other heuristic algorithms in terms of accuracy and convergence time.

3.2. Power take-off advancements

One of the most vital parts of designing and controlling wave energy converters is the PTO system. The design and control of a PTO system using different strategies can lead to the reduction in WEC's capital cost of energy (Pecher and Peter Kofoed, 2017) which can reduce the LCOE in the long run (Giassi et al., 2020a). In fact, optimizing a PTO system for a WEC in a layout has its own challenges for two main reasons. First, the irregular fluctuations in water-free surface elevation increase the level of uncertainty in further deterministic analysis. Second, unanticipated changes in WEC's location aquaculture may impose unpredicted forces on the converter, increasing or decreasing its displacement, velocity, or acceleration (Babarit, 2017). In recent years there has been some research on the optimization of PTO settings or control strategies coefficients (Parrinello et al., 2020; Neshat et al., 2019a; Penalba et al., 2017b; Ringwood et al., 2018; Amini et al., 2021). In this regard, a variety of power take-off systems has been designed and optimized in the recent literature, as shown in Fig. 15.

There are approximately 31 active companies in developing direct mechanical approaches in the world so far. For hydro-turbine, hydraulic system, air turbine, and direct electrical systems, these numbers decrease to 21, 13, 13, and 11 active companies, respectively. There are roughly nine other companies developing other power take-off systems that are not classified in this study (Raju, 2019).

As a standard approach, regardless of the deployed mechanical equipment, the PTO system of a wave energy layout is mostly designed as a linear spring–damper system, in which generating power is related to Coulomb damping (Göteman et al., 2020). Furthermore, using linear generators can facilitate the direct drive power take-off systems (Liu et al., 2020c). For instance, Vernier hybrid machines (Mueller and Baker, 2003), permanent magnetic synchronous generators (Elwood et al., 2010), switched reluctance linear generators (Pan et al., 2013), and flux-switching permanent magnet linear generators (FSPMLGs) (Huang et al., 2011, 2013, 2014) are appropriate to directly convert irregular oscillatory wave motions into unidirectional steady rotation of the generator and produce electricity. Another recent study (Dong et al., 2021) shows that the wave power is absorbed through the relative motion between the outer and inner cylindrical buoys in a 1:9 scaled model of a two-body heaving WEC. The conclusion is reached that greater relative movement does not imply stronger power capture. This system would benefit from a linear PTO damping system. Fig. 16 depicts three recent approaches for PTO parameters optimization regarding the use of Heuristic and metaheuristic algorithms.

As is illustrated in Fig. 16, three recently developed solutions for PTO optimization have been evaluated. First, an optimization studies EAs incorporating EASY software with two specific objective functions: (i) the total investment cost and (ii) the flow rate in the converter's reservoir. The research evaluates WEC's PTO and geometry variables by both single-objective and multi-objective functions shown in Fig. 16(a). In fact, the process tries to approach the maximum probable results in terms of total investment cost, flow rate, and annual water storage, according to the selected scenario in the Monterey Bay, California (Bonovas and Anagnostopoulos, 2020). Optimization of the system's design is performed using the general optimization software platform EASY, developed in the NTU Athens (Kapsoulis et al., 2018). The research addresses the inefficiency issues by proposing a more advanced piston head design with two functional diameters. This enhanced PTO design is found to increase by 30 percent of the annually stored energy in the reservoir (Bonovas and Anagnostopoulos, 2020).

In the second study flowchart, shown in Fig. 16(b), an HPTO model was configured considering the manufacturer's actual hydraulic component parameters. The numerical simulation and optimization process include Non-Linear Programming by Quadratic Lagrangian (NLPQL) and Genetic Algorithm (GA). Although the evaluations are performed for a single rotation-based WEC, the optimized values can be generalized to WEC arrays. The concluding remarks of this study prove the simulation–optimization time with the GA technique to be longer than with the NLPQL process in WEC-modeling problems (Jusoh et al., 2021). A much more comprehensive study of PTO hyper-parameters optimization in a WECs array, (Neshat et al., 2020c) suggested a new hybrid cooperative co-evolution algorithm including symmetric LS-NM and a cooperative co-evolution algorithm followed by a backtracking process for optimizing the locations and PTO settings of WECs, respectively. Fig. 16(c) depicts the proposed hybrid optimization system graphically.

After positioning the first buoy in a predetermined position, three optimizers are used to resolve PTO settings for each WEC in layout. Together, the findings confirm the hybrid cooperative system outperforms the others in terms of both runtime

Table 8
Layout study in regular and arbitrary patterns in the recent articles.

Author	Year	Type of Converter	WECs NO.	Patterns of layout	Master layout	objective of comparing layout	reference
Hamed Behzad	2019	OWSC	5	arrowhead up and arrowhead down, linear	arrowhead up	absorbed energy	Behzad and Sanaei (2019)
Ruiz	2017	Surging barges	25	optimized	–	annual power	Ruiz et al. (2017)
Giassi	2020	Point absorber	10-20-50	optimized	–	LCOE	Giassi et al. (2020a)
Fang	2018	Point absorber	3-5-8	optimized , line, triangle	–	absorbed energy	Fang et al. (2018b)
Giassi	2020	Point absorber	6	staggered, 2 aligned rows, b-shape	staggered, b-shape	performance	Giassi et al. (2020b)
Giassi	2018	Point absorber	4-5-7-9-14	optimized	–	power output	Giassi and Göteman (2018)
Baltisky	2014	OWSC	2-3-4-5-6	regular polygons	2 bodies (linear)	mean annual production	Balitsky et al. (2014)
Sharp	2015	Point absorber	5	optimized	–	power and cost	Sharp and DuPont (2015)
Bozzi	2017	point absorber	4	linear, square, rhombus	rhombus, linear	absorbed energy	Bozzi et al. (2017)
Moarefdoost	2016	Point absorber	2-3-4-5-6	optimized	–	q-factor	Moarefdoost et al. (2017)
Sharp	2018	Point absorber	5	optimized	–	power	Bharath (2018)
Neshat	2019	Point absorber	4–16	optimized	–	total power output	Neshat et al. (2020c,a, 2019a)
Wang	2020	Point absorber	6	triangle, Inverted triangle	triangle(one buoy faced incident wave)	annual power	Wang et al. (2020)
Ruiz	2018	overtopping	9	aligned, staggered, arrow	arrow	absorbed energy	López-Ruiz et al. (2018a,b)
Bosma	2020	OWC	5	staggered, optimized	optimized	average power	Bosma et al. (2020)
Borgarino	2012	cylinder barge	9-16-25	triangle, square	triangle	q-factor	Borgarino et al. (2012)
Giassi	2017	Point absorber	4-5-7-9	optimized	–	q-factor	Giassi and Göteman (2017)
Göteman	2015	Point absorber	60–100	3-5 C-shaped clusters	larger circles	power output	Göteman et al. (2015a)
Göteman	2015	Point absorber	250	random, rectangular, wedge, C-shaped	Circular (cable length), wedge (power)	cable length and power	Göteman et al. (2015b)
Mcguiness	2016	Point absorber	5-6-7	linear, circular	circular	q-factor	McGuinness and Thomas (2016)
Noad	2015	OWSC	3–5	linear, staggered, diagonal, bowl-like	bowl-like	absorbed power	Noad and Porter (2015)
Sharp	2017	OWC	5	optimized	–	generated power	Sharp et al. (2017)
Wu	2016	Point absorber	25-50-100	optimized	–	q-factor	Wu et al. (2016)
DeAndres	2014	Point absorber	2-3-4	linear, triangle, square, rhombus	square	q-factor	De Andrés et al. (2014)
Loukogeorgaki	2021	Point absorber	5	optimal linear	–	annual absorbed energy	Loukogeorgaki et al. (2021)
Neshat	2022	Point absorber	4–9	Optimized	–	annual power output	Neshat et al. (2022)

and consistency of obtained solutions. As a promising viewpoint, using optimization algorithms to enhance PTO coefficients has been developed recently. Neshat et al. (2020c) developed a new optimization framework called HCCA. It comprises a symmetric LS-NM, and a cooperative co-evolution method (CC) with a backtracking strategy. The study's objective was to optimize the positions and PTO settings of 4 and 16 WECs layouts, respectively. Since the PTO stiffness (K_{pto}) and damping (C_{pto} or D_{pto}) coefficients change over different frequencies, this problem turns into complex multi-directional optimization (Neshat et al., 2020c). Similarly, Yu et al. carried out another numerical study utilizing WEC-Sim solver for the same goal (Yu et al., 2018). Although the case studies are different, Fig. 17 compares both studies and gives us a better understanding of the power output trend proportional to other important variables.

As shown in Fig. 17(a), a specific range of frequency with tuned values of PTO coefficients can generate more power output. It can be observed that the overall trend of the power output rises over incoming wave frequency, reaching a maximum amount, and then plummets down to zero at higher frequencies. It certainly depends on the damping coefficient of the PTO system. This study carries out an optimization study to find the optimum value of this coefficient (Neshat et al., 2020c). Furthermore, by taking other buoys into account, the consequent interactions will increase the complexity of this plot. Although it was not verified with experiments, another experimental study, which is shown in Fig. 17(b), can approve the relation between power output and wave frequency. In this study, the power output is represented by capture width in both numerical simulation and wave tank experimental testing (Yu et al., 2018). It can be concluded that the more damping coefficient, the more maximum power output could be achieved in lower frequencies. Experimental results in Fig. 17 (c) confirms the above-mentioned idea in the

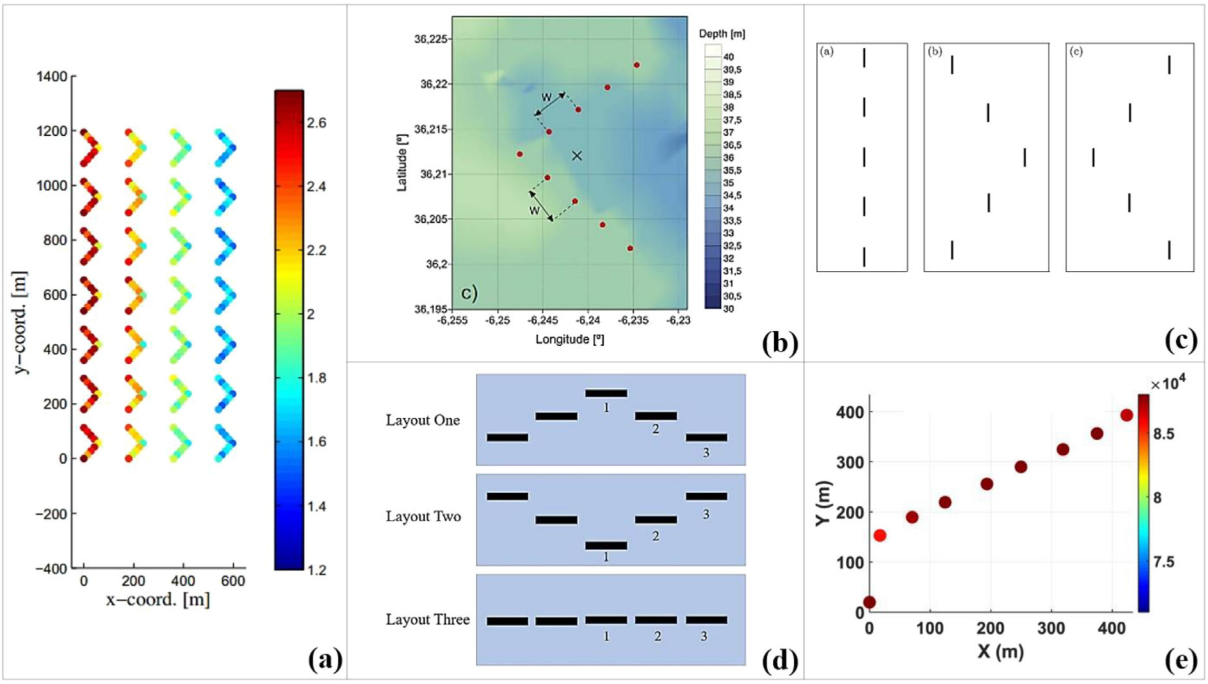


Fig. 13. Comparative point of view on Arrow (wedge) pattern of WECs, demonstrated in subplot (a) Göteman et al. (2015b) and (b) López-Ruiz et al. (2018b), together with a linear pattern of WECs in subplot (c) Noad and Porter (2015) and (d) Behzad and Sanaei (2019), and also the optimized layout (linear) in subplot (e) Neshat et al. (2020d) according to the recent papers.

first study. Moreover, the authors proposed an MMR-based PTO system for both prototype (test1 in Fig. 17(c)) and lab testing of PTO (test 2 in Fig. 17(c)). The results show that MMR-based PTO achieves better efficiency than nonMMR-based PTO for the rack pinion design by almost 25 percent at all frequencies (Zuo et al., 2021). This path is continued in a further study numerically and experimentally (Li et al., 2020a). Another similar study suggested a novel configurable electromechanical PTO, which allows setting its parameters for optimal power output according to wave scenarios. In Fig. 17(d), the study compares the effects of viscosity damping coefficients on averaged power output over wave frequencies. The resonance condition can be achieved in a specific condition regarding external frequency, and viscosity damping coefficient (Castro and Chiang, 2020). Moreover, Fig. 18 shows that a combination of both PTO parameters (damping $(d_1, d_2, \ldots, d_M)$, and spring's stiffness $(k_1, k_2, \ldots, k_M)$) make a multi-modal and complex search space and the optimal values associated with the wave frequency and model.

From a techno-economic point of view in analyzing the performance of PTO systems, levelised cost of energy (LCOE) is widely used to compare different technologies based on their production costs. It is also used within the wave energy sector to compare different devices. Based on a discount rate r and a design lifetime n, the LCOE defines the ratio of Capital Expenditures (CapEx) and Operating Expenditures (OpEx) to Annual Energy Production (AEP) as described in Eq.2 (Garcia-Teruel and Forehand, 2021a).

$$\mathrm{LCOE} = \frac{\mathrm{PV}(\mathrm{CapEx} + \mathrm{OpEx})}{\mathrm{PV}(\mathrm{AEP})} = \frac{\sum_{t=0}^{n} \left(\mathrm{CapEx}_t + \mathrm{OpEx}_t\right)/(1+r)^t}{\sum_{t=0}^{n} (\mathrm{AEP})/(1+r)^t}$$

This metric, however, is difficult to use during the early stages of design due to the lack of cost information. Other approaches for quantifying the trade-off between power generation and costs have been developed in order to facilitate device comparisons (Garcia-Teruel and Forehand, 2021a; Ringwood et al., 2018). We described the results of cutting-edge research in PTO setting optimization, which can also be used in WEC arrays. To address further challenges in this regard, more research may be required to fill the gap in optimizing the PTO coefficient over different frequencies. Because the optimization of a set of large WEC power take-off variables is a computationally costly, multi-modal, and large-scale problem, new algorithmic approaches would efficaciously reduce the computational budget. Furthermore, incorporating a smart module to set the PTO spring stiffness continuously in real-time and reducing sliding carriage friction could be another promising approach to enhancing current developments (Castro and Chiang, 2020; Liu et al., 2020c). Since this configuration may benefit LCOE, a detailed cost trade-off study would need to be performed (Yu et al., 2018; Balitsky et al., 2019).

$$\begin{array}{rl}
\min \mathbf{f}(\mathbf{x}) & \\
\text{objective functions}: & f_{(x)} \\
\text{decision variables}: & \mathbf{x} = \{x_1, \ldots, x_k\} \in \Omega \\
\text{equality constraints}: & g_i(\mathbf{x}) = 0 \quad \text{for } i = 1, \ldots, m \\
\text{inequality constraints}: & h_j(\mathbf{x}) \leq 0 \quad \text{for } j = 1, \ldots, l
\end{array}$$

$$\begin{array}{rl}
\min \mathbf{f}(\mathbf{x}) & \\
\text{objective functions}: & \mathbf{f}(\mathbf{x}) = \{f_1, f_2, \ldots, f_n\} \\
\text{decision variables}: & \mathbf{x} = \{x_1, \ldots, x_k\} \in \Omega \\
\text{equality constraints}: & g_t(\mathbf{x}) = 0 \ \ \text{for } i = 1, \ldots, m \\
\text{inequality constraints}: & h_j(x) < 0 \ \ \text{for } j = 1, \ldots, l
\end{array}$$

3.3. Geometric design

In Systematically analyzing the geometry optimization research projects, the key elements must define before the process begins. Firstly, we need to describe the definition and formulation of the optimizing process. By only considering one objective for this process, single-objective, the solution minimizes a defined objective function. Also, optimization problems mostly incorporate equality g and inequality h constraints. The single-objective problem can formulate as follows.

Considering more than one objective for the optimization problem, a multi-objective problem, there will be conflicting objectives that have not only multiple solutions but also the dependence of the objective function's weight on the final solution

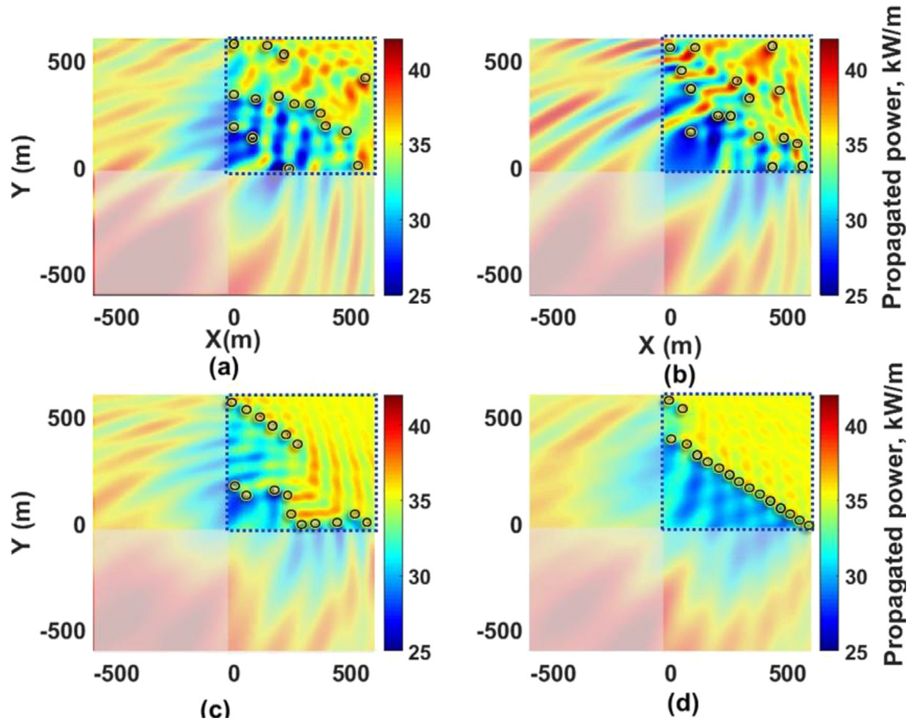


Fig. 14. The power landscape of the interpolated wave energy is based on the best-found 16 WECs layouts for the Perth wave model used by, (a) CMA-ES, (b) DE, (c) LS-NM and (d) ISLS(II)-AS. Black circles show the placement of WEC. (The wave angle propagates at 232.5°) (Neshat et al., 2020a).

can be considerable. Because there are multiple solutions without clear overcoming, a set of solutions will be sought in this process, which is called Pareto Front.

While increasing the absorbed energy from the WECs will increase profit, it may also increase the costs of the device. Therefore there should be a reasonable balance between these factors to achieve a competitive WEC design (Clark et al., 2019). Since WEC structure is one of the most important factors in minimizing project costs, to achieve this balance, many studies on WEC hull geometry optimization have been conducted to achieve this balance. A few of these studies are summarized here to provide an overview of general practices in this field (Garcia-Teruel and Forehand, 2021b; Neshat et al., 2020a).

First, we take a look at some studies on the geometry optimization of point absorbers. Babarit et al. carried out a multi-objective geometry optimization of the SEAREV device, a floating single body point absorber. Results showed that the largest draughts designs led to the most optimal performances (Babarit and Clement, 2006). Another study about a submerged single body point absorber was carried out, in which authors were able to reach significantly higher power output via hull design optimization of the device (Esmaeilzadeh and Alam, 2019). Another study investigated the optimal design of a floating single body point absorber with 3 different float shapes, using an exhaustive search method. Results showed that despite the fact that the smallest ratios of draft to radius of the floats led to the maximum power output; in 2 of the three investigated cases, it did not lead to the most economical design.

Furthermore, they found that increasing the mass of the float did not have a meaningful effect on the power output of the WEC (Erselcan and Kükner, 2020). Gomes et al. optimized the hull design of a two-body point absorber using a GA to maximize the extracted energy, but the obtained dimensions of the WEC were impractical. As a result, they changed their objective function to the ratio of the absorbed energy to immersed volume of the WEC and found a more practical solution. It was found that increasing the length of the floater has no significant effect on the annual power output (Gomes et al., 2010). In another study, an evaluation of a two-body point absorber was carried out using the Taguchi method in order to increase the power output. The shape of the immersed body was found to be the most important factor in determining power output. Additionally, the buoy diameter and the immersed depth were less critical factors (Al Shami et al., 2019). The typical geometric designs of one-body and two-body point absorbers are surveyed by Guo and Ringwood (2021), shown in Figs. 19 and 20, help us classify the recently developed shapes of such WECs.

The next class of WECs that its hull dimensioning will get a brief review here is OWCs. Bouali et al. optimized the geometry of a fixed OWC using a Sequential Procedure, in which they optimized the first parameter, kept it constant, then found the optimal value for the second parameter, etc. They were able to reach an improvement of 7% in performance (Bouali and Larbi, 2017). Likewise, the geometry of a floating OWC was optimized by Gomes et al. to maximize the energy output. It was found that the floater's diameter, the immersed length, and the height of the air chamber can affect the annual power output significantly (Gomes et al., 2012).

Next, we will look at two studies optimizing the WEC dimensioning of an OWSC similar to the Oyster. Noad et al. were able to reach an increase of 15% in the device's capture factor by decreasing the hinge depth of the device. However, it resulted in big oscillations in the device's flap, which in turn brought out some inaccuracies in calculations. Therefore, they did not use this design in further simulations (Noad and Porter, 2015). Renzi et al. were able to increase the capture factor by approximately 50% and almost reach a capture factor of 1 (Renzi et al., 2017).

Another class of the WECs is the attenuators. Colby et al. optimized the geometry of an attenuator WEC, which consists of the design of a spar, a forward float, and an aft float to maximize the annual energy extracted. First, they tried to incorporate a few ballasts and tried to optimize the cuts needed to make the necessary chambers, which led to a 17% increase in the objective function. Then they attempted to utilize the ability to fill or

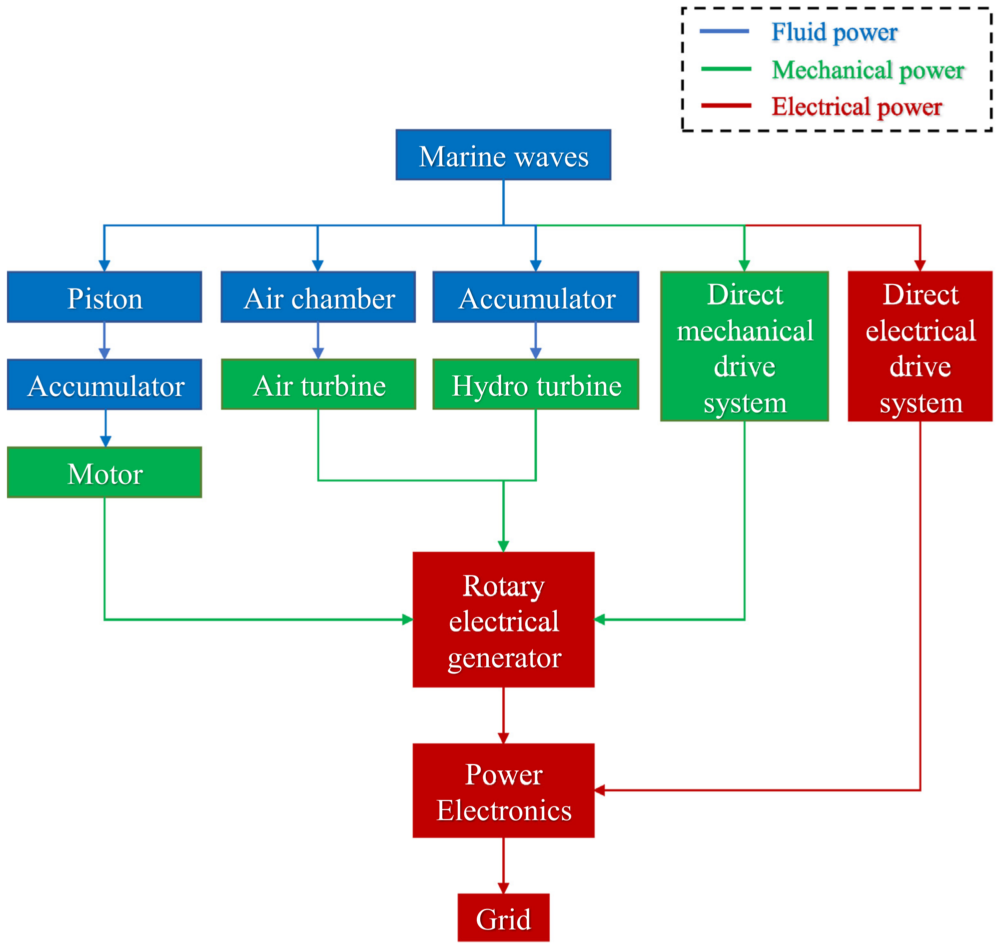


Fig. 15. Different parts and routes of energy conversion in a power take-off system, from wave to grid.
Source: Adapted from Pecher and Peter Kofoed (2017).

empty the ballasts, to change their mass parameters, and with a control loop time, they were able to reach an 84% improvement in performance (Colby et al., 2011). Likewise, Wang et al. carried out a study to optimize the design of a hinge-barge, which worked as an attenuator, to maximize the energy output using the control-informed geometric design (CIGD) approach, which improved the performance by 22% (Wang and Ringwood, 2019).

The last type of WECs reviewed in this section is the Overtopping WECs. Martins et al. optimized the geometry of a generic Overtopping WEC, using the Exhaustive Search Method to maximize the power output. They tried to change the overtopping ramp slope and the distance between the device and the wave tank bottom. They found a negative relationship between the ramp slope and the device's performance (Martins et al., 2018). Margheritini et al. showed that the geometry of an Overtopping WEC could increase the device's performance up to 30% (Margheritini et al., 2012). More information about WEC geometry optimization studies is presented in Table 9.

Considering the design constraints, the dimensions of the WEC hulls were optimized mainly to improve the performance and reduce the hull size, i.e., cost. Results showed that geometry optimization could significantly improve the absorbed energy (Esmaeilzadeh and Alam, 2019; Gomes et al., 2012; Renzi et al., 2017; Colby et al., 2011). If the PTO control strategy is optimized simultaneously with the geometry using multi-objective optimization, it may result in better solutions (Garcia-Teruel and Forehand, 2021b). Although increasing the dimensions of the WECs can potentially result in better performance, it does increase the costs of the operation as well. Thus, there is a trade-off in design between absorbed power and costs that should be addressed.

4. Future directions of WEC's optimization

The WEC optimization research is currently at a critical phase in its advancement. It faces a large number of challenges that require investigation to re-orientate on an adaptable techno-economic perspective. It also needs the technical improvements of WECs optimization frameworks for niche markets as there are imbalances on the global scale concerning wave energy resources.

Another leading research gap in developing optimization methods for WECs is considering the various aspects of technological or non-technological investment risks and uncertainty in LCOE models. This goal can be achieved by developing multi- and many-objective optimization frameworks based on interdisciplinary studies, combining considerable knowledge of ocean engineers, environmental scientists, economists, and policy specialists.

Furthermore, the number of optimization studies on large-scale wave farms is a few compared with small size (<10 WECs). This is mainly due to many decision variables, the multi-factorial nature of this optimization problem, complex and multi-model search spaces, the computational cost of the modeling and test-

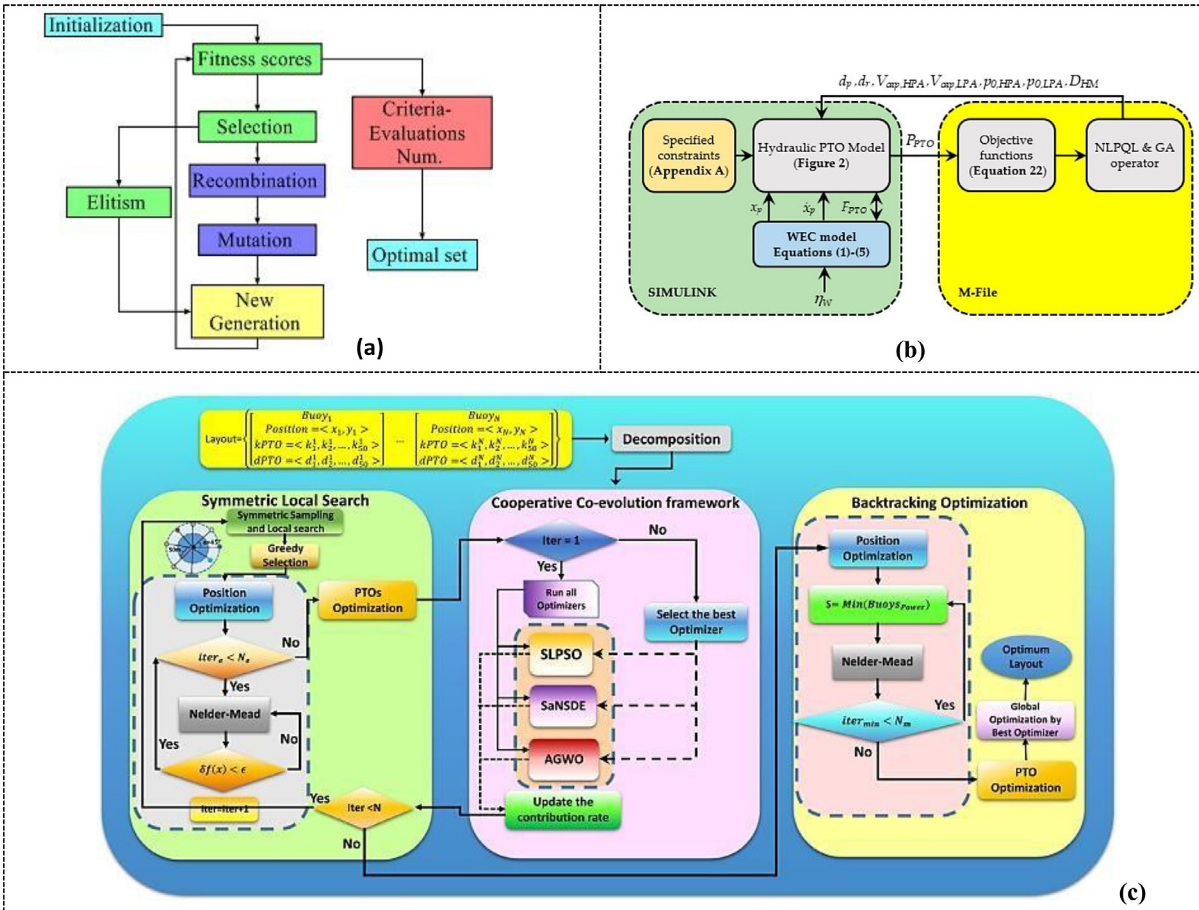


Fig. 16. Optimization process flowcharts of three recent studies on PTO parameters optimization. (a): optimization flowchart of constructive parameters in EASY software using EAs (Bonovas and Anagnostopoulos, 2020). (b): Illustration of optimization model set-up in MATLAB software using NLPQL and GA optimizer (Jusoh et al., 2021). (c): Outline of the HCCA for PTO hyper-parameters optimization (Neshat et al., 2020c).

Table 9
Optimization studies about WEC hull design.

Author	Year	Type of converter	optimization algorithm	Objective function	optimized dimensions	Reference
A. Babarit	2006	Point Absorber	Genetic Algorithm	Absorbed Power, Cost	the Length, the Beam, the Draught	Babarit and Clement (2006)
S. Esmaeilzadeh	2019	Point Absorber	Genetic Algorithm	Power Output	Elongation Coefficients of the Base Shape of the WEC	Esmaeilzadeh and Alam (2019)
B. Bouali	2017	OWC	a Sequential Procedure	Hydrodynamic Efficiency	the Immersion Depth, Width of the OWC Chamber Front Wall	Bouali and Larbi (2017)
R.P.F. Gomes	2012	OWC	COBYLA, DE	Energy Absorption	Length and Diameters of the Small and Large Thickness Tubes	Gomes et al. (2012)
I.F. Noad	2015	OWSC	–	Capture Factor	Length, Width of the Flap, Hinge Depth	Noad and Porter (2015)
Emiliano Renzi	2017	OWSC	Genetic Algorithm	Capture Factor	Flap Width, Water Depth, Hinge Height	Renzi et al. (2017)
Mitch Colby	2011	Attenuator	Evolutionary Algorithm	Annual Power Output	Design of Ballast Chamber Cuts, Weight Distribution	Colby et al. (2011)
Liguo Wang	2019	Attenuator	Exhaustive Search Method	Extracted Energy	Lengths of the Fore and Aft Barges	Wang and Ringwood (2019)
Liguo Wang	2021	hinge barge WEC	GA	Mean Power Output	Geometry of fore and aft barges	Wang and Ringwood (2021)
Mehdi Neshat	2021	fully submerged Point absorber	Improved Moth–Flame optimization	Total Power Output	Dimension of the cylinder height over the radius	Neshat et al. (2021)

ing process (in some cases taking one day per evaluation), a large number of complex constraints and the tribulation of modeling dynamic designs.

Considering novel optimization concepts such as exploring a diverse set of high-quality solutions (Pareto Diversity Optimization (Neumann et al., 2022; Do et al., 2022)) instead of focusing

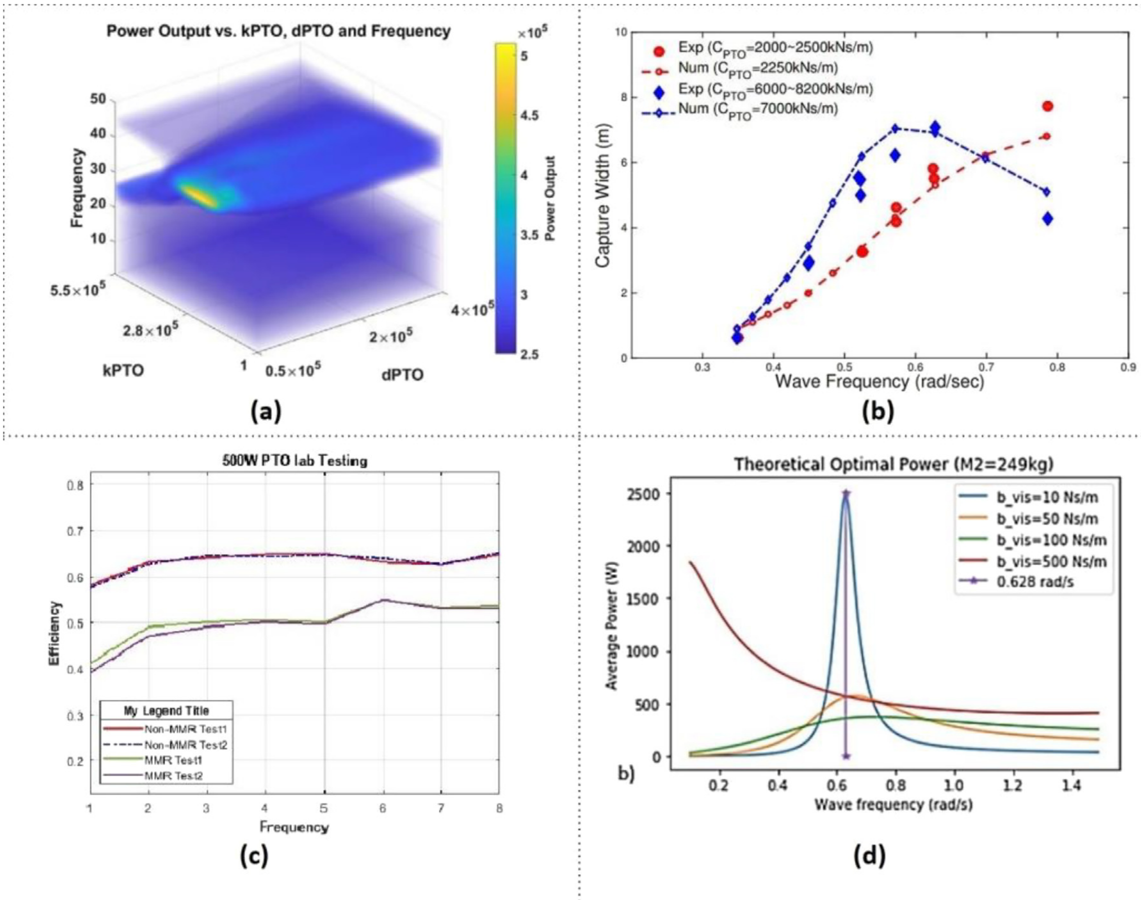


Fig. 17. Comparing two studies on the effects of PTO coefficient changes on the power output of wave energy converter. (a): 4D view PTO power landscape for a buoy in a layout in the Australian coasts, results from a numerical optimization study (Neshat et al., 2020c). (b): Capture width ratio (harnessed power divided by the wave power) over the course of frequency (Yu et al., 2018). (c): Lab-testing results over frequency, using MMR-based and non-MMR-based power take-off system (Zuo et al., 2021). (d): Average power versus external frequency with optimal C_{pto} and K_{pto} in different linear viscosity damping coefficients (Castro and Chiang, 2020).

on just a single optimal solution can open a new insight into wave energy systems' optimization. Future research and development of WEC optimization need to be enhanced by applying modern computational tools (using GPUs instead of CPUs) and state-of-the-art smart methods.

Due to the challenges of single-objective optimization of wave energy converter parameters, multi-objective optimization is often beneficial for practical WEC design studies. With a multi-objective study, a set of responses may be selected without assessing relative weighting factors, which may be challenging. The power take-off variables will also be better understood by examining how they interact and are controlled to attain significant performance improvements in a multi-objective optimization study. This may include the development of a feed-forward and feed-back control approach.

5. Conclusion and remarks

Researchers mostly provide information about the types of evidence that affect and inform practice and the methodological methods used in cutting-edge research in the form of a scoping review. With regard to wave energy conversion investigations and due to the notable considerable potential of the produced energy from ocean waves in the near future, the development and progression of wave energy technologies are high. WECs technologies need more developments to be commercialized compared to other renewable energies. In order to achieve the maximum generated power using wave energy converters (WECs), layout and PTO optimization play a significant role. However, optimizing them is challenging because of the complex hydrodynamic interactions among converters.

In this scoping review, firstly, we discuss the different classifications of converters introduced by Drew et al. (2009), Aubry et al. (2011), Antonio (2010) and other researchers which we believe that the classification based on working principles together with the hydromechanical conversion system is superior one on the grounds of generality as well as considering other distinctive factors. An overview of numerical methods and solvers to unravel the hydrodynamic interactions is given. After that, we enumerate the recent articles that used at least one of the methods in their study. We believe that understanding the cause of interaction between WECs and applied forces for the selected converter type must be accurately assumed to start the study, and then a low or high fidelity approach should be selected according to the scale and required accuracy of the project. Next, a survey on optimization problems is done because of the increasing number of algorithms and objective functions studied by the researchers in this field. It is concluded that most research focuses on using GAs with only one objective function. The number of studies related to multi-objective optimization is low. We believe that the use of ANSO, HCCA, and in general, local search methods with backtracking optimization can enhance the optimization accuracy. A summary of conclusions about the layout optimization 3.1, and geometry optimization 3.3 are as follows.

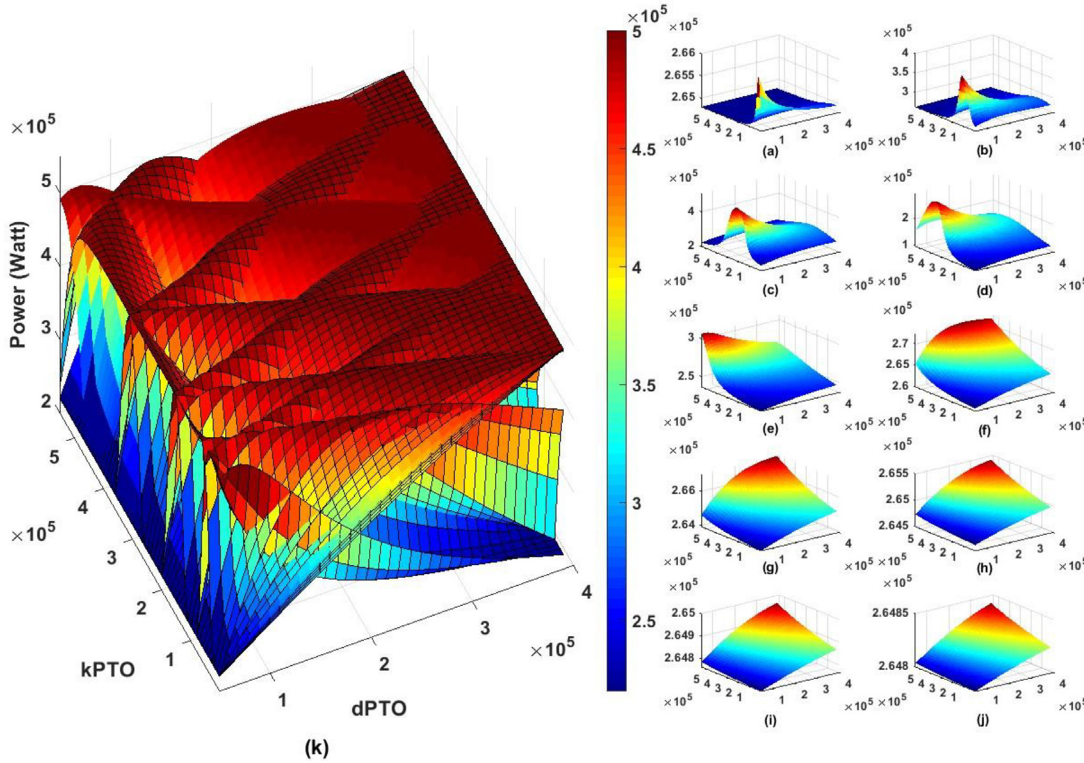


Fig. 18. The power landscape analysis (Neshat et al., 2020a) of one WEC with two PTO control parameters: damping ($d_1, d_2, \ldots, d_{50}$) and spring ($k_1, k_2, \ldots, k_{50}$) coefficients. Figure (k) is a combination of ten PTO power landscapes from Figure (a) to (j). Figure (a) shows a 3D power analysis of one WEC with different PTO configurations where the initial five k and d parameters are assigned using a grid search and remained ones (45 PTO parameters) are kept fixed as predefined PTO values ($d = 97412$, $k = 407510$). Other figures follow the same pattern.

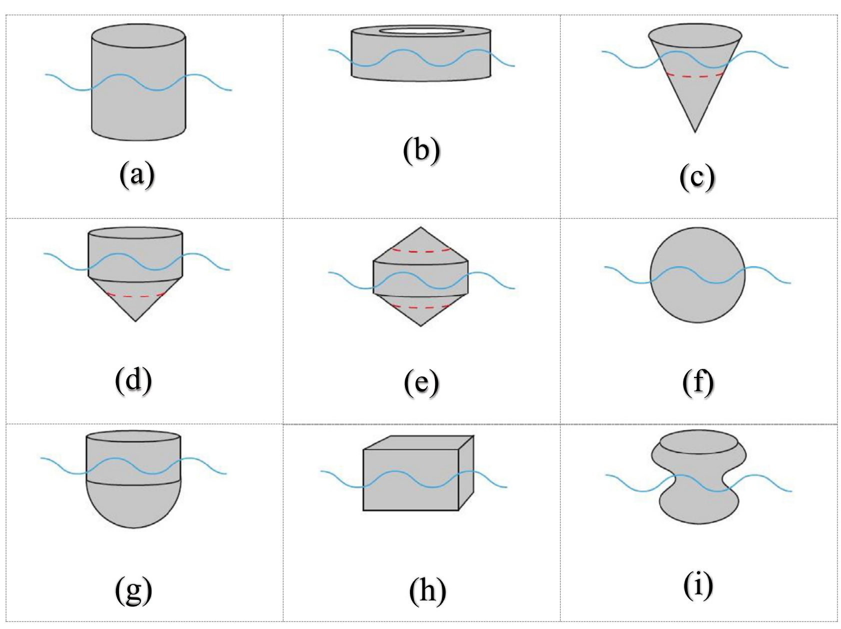


Fig. 19. Classification of geometric shapes for one-body point absorbers. a: Cylinder, b: Cylinder–moonpool, c: Cone, d: Cylinder–cone, e: Cone–Cylinder–cone, f: Sphere, g: Cylinder–sphere, h: Cuboid, i: Arbitrary shape (Guo and Ringwood, 2021).

- Layout optimization studies have a wide range of discussions about relative factors to reach the optimal answer. This paper represents two patterns (linear, arrowhead pattern) as the most repetitive viable results in reviewed studies. Factors such as distance and wave direction directly affect the layout performance. So we share an overall statement on these factors (increasing or decreasing) in determining the array layout.
- Studies show that geometry optimization of the WECs can improve performance notably. Better results can achieve through geometry optimization in combination with the PTO control strategy. While enhancing the geometry of the

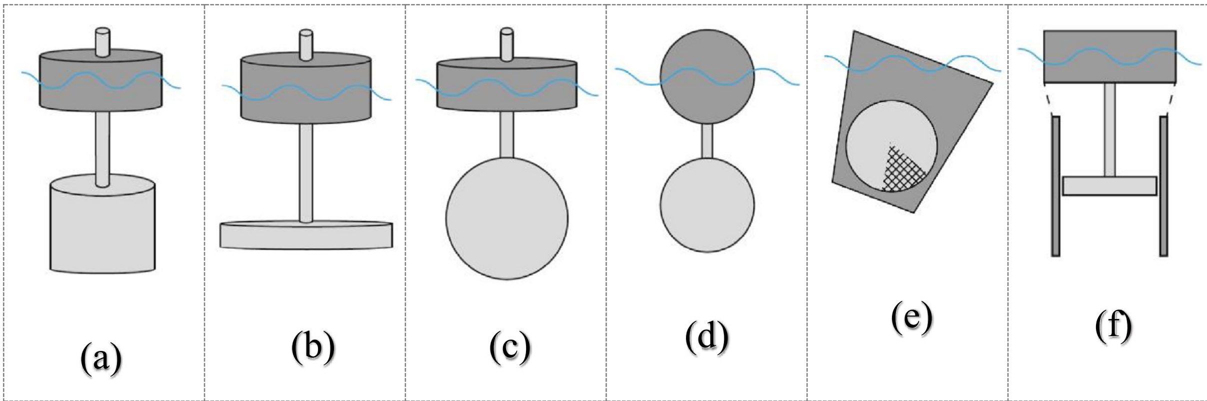


Fig. 20. Classification of geometric shapes for two-body point absorbers. a: Cylinder–cylinder, b: Cylinder–plate, c: Cylinder–sphere, d: Sphere–sphere, e: Hull-pendulum, f: Cylinder–piston (Guo and Ringwood, 2021).

WECs will increase the profit and should optimize performance regarding the increased costs.

In the end, we believe that further research on multi-objective studies that especially consider cost and maximum absorbed energy are more likely to add valuable results and understanding in the future. Furthermore, numerous studies that use CFD rather than BEM as the numerical method are sensed among the published papers. The number of articles using GA is high, so we suggest using other robust metaheuristic algorithms that can return better answers in a shorter time. Finally, we wish to see further studies aiming to address the mentioned issues in the future.

Abbreviations The following abbreviations are used in this manuscript:

WEC	Wave Energy Converter
PTO	Power Take-off
LCOE	Levelized Cost of Energy
CFD	Computational Fluid Dynamics
OWC	Oscillating Water Column
WES	Wave Energy Scotland
TWh	Terawatt hour
DOF	Degree of Freedom
PF	Potential Flow
DNS	Direct Numerical Simulation
LES	Large Eddy Simulation
SPH	Smoothed Particle Hydrodynamics
RANS	Reynold-Averaged Navier–Stokes
BEM	Boundary Element Method
COBYLA	Constrained Optimized by Linear Approximation
NLPQL	Non-Linear Programming by Quadratic Lagrangian
ANSO	Adaptive Neuro-Surrogate Optimization
LS-NM	Local Search plus Nelder–Mead
HCCA	Hybrid Cooperative Co-evolution Algorithm
GA	Genetic Algorithm
GP	Genetic Programming
DE	Differential Evolution
SA	Simulated Annealing Algorithm
CMA	Covariance Matrix Adaptation
CMA-ES	Covariance Matrix Adaptation based Evolutionary Strategy
NM	Nelder–Mead
EA	Evolutionary-based Algorithms
PSO	Particle Swarm Optimization
SCA	Sine Cosine Algorithm
ACO	Ant Colony Optimization
ABC	Artificial Bee Colony
MFO	Moth–Flame Optimization
MVO	Multi-Verse Optimizer
GWO	Grey Wolf Optimization
SSA	Salp Swarm Algorithm
DA	Dragonfly Optimization
WOA	Whale Optimization Algorithm
EO	Equilibrium Optimizer
ALO	Ant Lion Optimizer
WCA	Water Cycle Algorithm
ICA	Imperialist Competitive Algorithm
GSA	Gravitational Search Algorithm

CRediT authorship contribution statement

Danial Golbaz: Conceptualization, Methodology, Visualization, Writing – original draft. **Rojin Asadi:** Resources, Writing – original draft, Visualization. **Erfan Amini:** Conceptualization, Methodology, Visualization, Writing – original draft. **Hossein Mehdipour:** Writing – original draft. **Mahdieh Nasiri:** Editing original draft. **Bahareh Etaati:** Visualization, Writing – original draft. **Seyed Taghi Omid Naeeni:** Supervision, Editing original draft. **Mehdi Neshat:** Conceptualization, Visualization, Investigation, Writing – original draft, Writing – review & editing. **Seyedali Mirjalili:** Supervision, Conceptualization, Writing – review & editing. **Amir H. Gandomi:** Supervision, Conceptualization, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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