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Tuning of Fuzzy Logic Controller Using an Improved Black Hole Algorithm for Maximizing Power Capture of Ocean Wave Energy Converters

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Abstract

Seas and oceans are the most important sources of renewable energy in the world. The main purpose of this paper is to use an appropriate control strategy to improve the performance of point absorbers. In this scheme, considering the high uncertainty in the parameters of the power take-off system in different atmospheric conditions, a new improved black hole algorithm is introduced to tune fuzzy controller parameters for controlling and tracking the power. In order to demonstrate validity and performance of the proposed algorithm, simulations are performed for some benchmark functions. The proposed method is then implemented for tuning the fuzzy controller parameters in order to obtain the maximum power capture of wave energy converters. Compared to particle swarm optimization and conventional black hole algorithm, the results of the proposed method indicate enhancements in reference speed tracking and absorbed power.

Keywords: wave energy converter, fuzzy control, improved black hole algorithm, uncertainty
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1. Introduction

Seas and oceans are considered as the greatest sources of energy. Access of countries, including developing countries, to a variety of energy sources for their economic development is essential to their progress. Global energy consumption is projected to increase by 40% in 2050 compared to 2010 [1]. Given that energy sources are limited, this huge amount of demand will not be satisfied in the near future. Thus, renewable energy sources will play an important role in the future. Using renewable energy in recent decades has been considered as an appropriate solution to some environmental problems related to growing energy demand and global warming. Seas and oceans are important sources of energy if large amount of water is efficiently exploited, they will be a major source of energy for that country. There are six important sources of renewable energy in the oceans: waves, tides, ocean currents, thermal gradient, salinity gradient and biomass. In fact, wave energy can be considered as a concentrated form of solar energy. Ocean water is in steady motion; the gravitational pulls of the Sun and the Moon leads to tidal bulges in the Earth's ocean water once a day (producing two tides a day), and the wind drives these to the waves (Fig. 1).

Experts [2] express that the global potential of the enormous energy of sea and ocean water is estimated to be about two terawatts. The reasons for using this energy can be summarized as follows:

– Wave energy is one of a variety of renewable energies with a high energy density and low environmental impact compared to the other energies.

– Wave energy prediction possibility is far higher than solar energy and wind power.

– Generation of electricity from wave energy can be done continuously overnight, and waves can travel long distances with very low energy losses.

According to the energy distribution in different parts of the world (Altas, 2017), Table 1 shows that Asia and Australia exploit the highest amounts of wave energy; South and North America also exploit significant amounts of power.

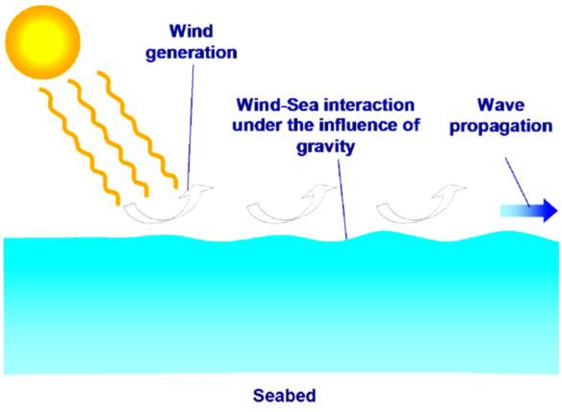

Fig. 1. How to produce waves.

Table.1.
Theoretical potential of regional wave energy exploitation.

Region	***Wave energy TWhh/yr***
Western Europe and North	2/800
The Mediterranean and the Atlantic	1/300
North America and Greenland	4/000
Central America	1/500
South America	4/600
Africa	3/500
Asia	6/200
Australia, NewZealand,Pacific Islands	5/600
Total	29/500

The investigations of different concepts related to wave energy converters (WECs), such as wave conditions (regular and irregular wave), type of oscillating bodies, (oscillating columns and overtopping), type of generator (nonlinear and linear), controlling system (mechanical and electrical) and the electronic power topology, has led to a variety of research papers on simulation and experimentation in this field; these researches are briefly summarized in Fig 2.

One of the most important issues that wave power plants confront is how to control WECs to generate maximum power. Thus, it is necessary to design controllers that can control the oscillations of transducers when they encounter waves. Several studies have been conducted on controlling wave power converter systems and maximizing power output in various applications [3]. Fuzzy logic controllers have been employed by the industry because of their simplicity and usability in nonlinear systems. In addition, these controllers are independent of the mathematical model of the system.

In [4], a new technique is proposed for controlling the power efficiency of wave-energy converters in which self-regulating fuzzy controllers employed to maximize power absorption by considering some constraints.

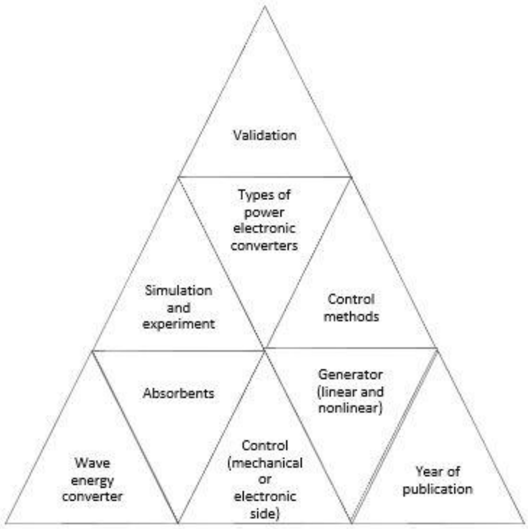

Fig. 2. WEC structure classification (Altas, 2017).

In the early 1980s, Baudal and Fallens [5] showed that, for maximizing the energy absorbed in aWEC, it is necessary to keep the velocity in phase with the excitation force. As a result, a particular type of phase control was introduced called the latching control. Applying a latching controller to a converter involves locking the floating motion in an instant when the speed is set to zero, and then releasing the transducer at the expected time, called the latching time [6]. During the latching time, the converter system is locked and stationary, and after this time period, the system is re-released. Accordingly, the velocity and excitation force are kept in phase, so they the absorbed power is maximized [7].When the power take-off (PTO) system is used to convert the mechanical energy of the sea wave into useful electric energy, it requires force control. In [8], two methods are proposed for controlling the force applied by the hydraulic PTO system. The first method is a quasi-continuous control and the second one is a declutching control. Quasi-continuous force control methods can be approximated by a set of discrete values, which lead to the complexity of the PTO. The turbo-generator module is usually fed by a simple proportional-integral (PI) controller that requires comprehensive knowledge about system parameters, constraints, and in some cases, the power output of the system. To prevent such constraints, a control method has been introduced using the sliding mode controller for an oscillating blue pillar system. In this method, to obtain the maximum output power, the speed of the generator turbine shaft must be adjusted. A sliding mode controller is used to regulate the generator slip and provides a high frequency switching control method for nonlinear systems in the presence of uncertainty [9]. In [10], a robust control method is presented for enhancing the energy extracted from floating WECs. The purpose of the controller is power optimization and using a control strategy that includes upper and lower control levels. The high-level controller produces the reference speeds that are used by the low-level controller to adjust the actual speed of the float. In [11], the optimal control schemes applied to the point absorber converter with the prediction horizon, which move only upward and downward, are examined. A variation formula for maximizing the power is accepted for solving the optimal control problem. In this paper, a bang-bang type optimal control method is used for a power start mechanism, which includes linear damper and active control elements; it also directly copies the optimal control problem as a non-linear problem. In WECs, there are many uncertainties due to the unpredictability of wave height and diverse weather conditions in different seas. Choosing the right type of controllers can, to some extent, resolve the way of dealing with these uncertainties. Different control methods in the references [10], [3] and [2] have investigated setting the parameters of the system, each having its own advantages and disadvantages. Table 2 lists the control methods that have been investigated so far. Although the control method presented in the present article is public and can be used for a wide variety of WECs, a specific WEC is studied here. The WEC studied in this paper uses the principle of point-of-attraction, as shown in Fig. 3 [12].

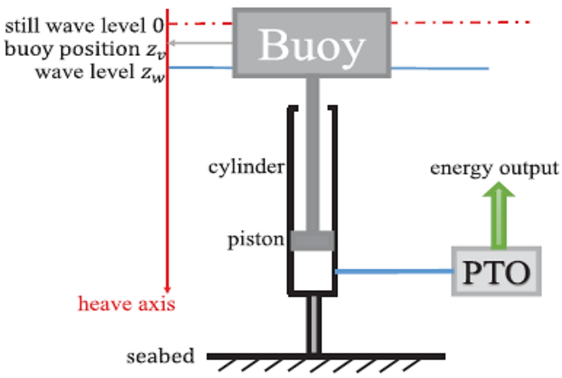

Fig. 3. Schematic of point absorber

According to the characteristics of fuzzy controllers mentioned in the literature (independency on model and protection against uncertainty), in this paper, fuzzy controller parameters that are adjusted using a new improved black hole algorithm are exploited to control a point absorber WEC. The purpose is to track the reference speed of the point absorber for maximizing the generated power. In order to investigate the new improved black hole algorithm, first, its performance on benchmark functions is compared with particle swarm and conventional black hole optimization algorithms. Then, this algorithm is applied to the problem of fuzzy controller parameter adjustment of a WEC. Simulations are performed using MATLAB.

The article is organized as follows. Section 2 describes WECs. Section 3 explains how to convert waves into electricity. The WEC state-space model is then described. In Section 4, the fuzzy controller strategy, which is adjusted with the proposed improved black hole algorithm, is explained. In Section 5, first, the simulation results of the proposed algorithm implemented on benchmark functions are presented, and then, the simulation results of a point absorber WEC are presented. Finally, the conclusion remarks are given in Section 6.

Table.2.
Summary of tools to deal with uncertainties, their benefits and disadvantages.

Artificial Neural Networks	***Predictive Controller***	***Adaptive Control***
Suitable for complex systems	Design based on the exact model of the system	Robustness of the system parameter uncertainty
Suitable for problems with unknown dynamics	Suitable for nonlinear systems	More convergence speed in approaching to set point
Identifying the model of the system	Suitable for constrained problems	Ability to adapt to system uncertainties
Learning the network may be difficult or even impossible.	Online system control	High computing volume and high implementation cost
Processing volume of the information	Approximation of the turbulence model	It is not suitable for fast uncertainties
Accuracy of the results depends on the size of the training set.	Conclusion is complicated	System depreciation due to fast update of parameters
Type 2 fuzzy controller	Sliding mode controller	Fuzzy controller
Use of language phrases that cannot be measured	Suitable for nonlinear systems	Based on human experience
Non-constant noise modeling	Phenomenon of chattering problem	Suitable for uncertainty
Accurate modeling of systems with high uncertainty	Problem of instability of asymptotic time limited	Suitable for super-nonlinear mode
Ability to describe variable time systems	Inappropriate for uncertainties	Lack of accurate modeling of systems with high uncertainty

2. Wave Energy Converters

Wave-energy devices are located in three different oceanic environments: onshore, nearshore and offshore, as shown in Figure 7. The strengths and weaknesses of each location are explained as follows:
2-1- Onshore devices: The design of this type of converters uses the integrated low cost structures;

moreover, they are close to the maintenance network and can be relatively easily accessed. These converters are less damaged due to less exposure to seawater. However, the power output of this type of transducers is low due to exploiting short waves.

2-2- Nearshore devices: This type of devices are fixed at depths of 10 to 25 meters from the sea surface. Their disadvantages are similar to those of onshore devices.

2-3- Offshore devices: These devices are installed and deployed in deep waters, making them expensive and difficult to maintain, but the maximum power output of this type of converters is maximum.

In this article, a nearshore point absorber WEC at a depth of 15 meters is considered. Table 3 shows the characteristics of different types of WECs that are categorized based on their location in the ocean.

3. Ocean to Power Model

The term "ocean to power" is one of the important parts of the process of generating electricity by sea/ocean waves; "ocean" implies the waves in the ocean as the input of the system, and "power" refers to the output. A challenge associated with the input of energy converters is the inaccuracy of the input due to the nature of the ocean waves, and a challenge with the output is the generation of electricity and injecting it into the network. Therefore, to overcome these issues, a WEC system has to be able to absorb the mechanical energy from the ocean waves and efficiently convert the absorbed energy into electrical power. In general, the main functions of electrical power converters for a WEC system are:

$$f_{ex}(t) - f_r(t) - f_b(t) - f_{loss}(t) - f_{rs}(t) - f_m(t) - f_d(t) + f_u(t) = m\ddot{z}(t) \quad (1)$$

Converting different types of electrical energy, e.g., from AC to DC,Increasing generation of power from ocean waves ,Controlling the power quality of the output waveform, making it suitable for commercial use.

In general, the components of WECs are as follows: the primary recording system, the PTO system and the lateral system of the network (electronic power converters). In this paper, a nearshore point absorber WEC at a depth of 15 m from the ocean surface is considered.

The mathematical model of the point absorber WEC system is complicated and nonlinear. Under certain assumptions, the forces applied to the converter are generally divided into two groups [2]. The first group include hydraulic forces that are exerted by the water surrounding the buoy, and the second group include forces exerted on the buoy by other components of the converter, such as the PTO and spring forces. Because our plant is prone to uncertainty when waves strike, and other phenomena, such as looseness, friction and saturation, may affect the system, a nonlinear model will be used.

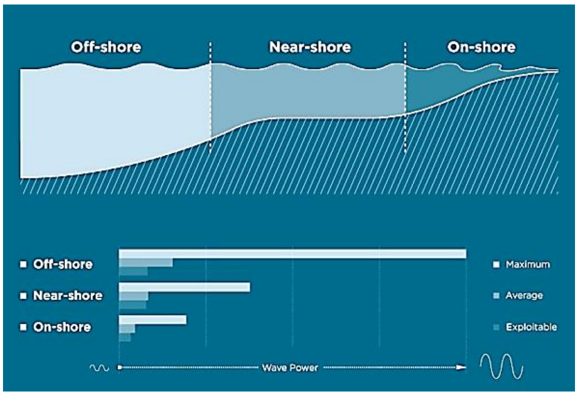

Fig. 4. Types of WECs in terms of location

Table.3.
Types of WECs in terms of location

Location	System type	Explanation	
		Advantages	Disadvantages
Onshore	Oscillating water columns(OWC) Overtopping devices	Easy maintenance and installation They do not require long electrical cables under water	Low wave power in shallow water
Nearshore (10-25 m deep)	Oscillating wave surge converters Point Absorbers Submerged Pressure Differential devices	Advantages and disadvantages of onshore with moderate intensity	
Offshore (>40 m deep)	Attenuators Bulge wave devices Rotating mass converters	The power output is maximized according to the power of the wave	High costs of maintenance and power transfer to the desired location

The equations that govern the motion of the point absorber buoy are derived from Newton's second law as follows:

where m is the sum of physical masses of the buoy, connecting rod and permanent magnet linear generator; $\ddot{z}(t)$ is the motion acceleration of the buoy, $f_{ex}(t)$ the wave excitation force, $f_r(t)$ the wave radiation force, $f_b(t)$ the hydrostatic buoyancy force; $f_{loss}(t)$ the mechanical and hydrodynamic losses, $f_{rs}(t)$ the force applied by the spring-like section;

$f_m(t)$ is the nonlinear mooring force, which holds the converter fixed; $f_d(t)$ is the nonlinear drag force, and $f_u(t)$is the mechanical control force applied by the PMLG (PTO section). In this article, $f_u(t)$ is calculated by a type-2 fuzzy controller, as explained in Table 4.

Table.4.
Describing linear and nonlinear forces of the system under study.

force	formula	Description
$f_r(t)$	$f_r(t) = m_\infty \ddot{z} + \int_0^t k_r(t-\tau)\dot{z}(t)d\tau$	Hydrodynamic radiation force $f_r(t)$ is a force whose output is dependent only on the input values in the present and past (not future); m_∞ is the infinite-frequency added mass, and the second term is estimated using a nonlinear model
$f_d(t)$	$f_d(t) = 0.5\,\rho A_w C_d \lvert\dot{z}(t)\rvert \dot{z}(t)$	Drag force ($f_d(t)$) acts on an object that moves through a fluid and is considered as a nonlinear force.
$f_{ex}(t)$	$f_{ex}(t) = K_{ex}(t) * \gamma_1(t) \int_0^t k_{ex}(t-\tau)\gamma_1(t)d\tau$	Hydrodynamic wave excitation force is applied by the waves to a buoy and is considered as the main force acting on the wave-converter system.
$f_b(t)$	$f_b(t) = \rho g A_w z(t) = S_b z(t)$	Buoyant force $f_b(t)$ is equal to the weight of the fluid displaced during oscillations of an immersed buoy.
$f_u(t)$	$f_u = -R_U \dot{Z}(t) + S_U Z(t)$	An under control force that is exerted by the power take-off system on the converter, and intends to generate the maximum power.
$f_{rs}(t)$	$f_{rs}(t) = S_{rs} z(t)$	Restoring force is a linear force that is created by the springs between the buoy and the power take-off system under water**.**
$f_{loss}(t)$	$f_{loss}(t) = R_{loss}\dot{z}(t)$	A force that results from the friction and non-ideal performance of the system**.**
$f_m(t)$	$f_m(t) = 2S_m Z(t)(1 - l_m\sqrt{{l_m}^2 + z(t)^2})$	A nonlinear force that is used to keep the point absorber converters at a fixed location.

Table 1. Describing linear and nonlinear forces of the system under study.

By inserting the forces of Table 4 into Eq. (1) we have:

$$\ddot{z}(t) = \frac{1}{m+m_\infty}\Big[f_{ex} + f_u - C_r q_r(t) - (s_b + s_{rs})z(t) - R_{loss}\dot{z}(t) - 2S_m Z(t)\Big(1 - l_m\sqrt{{l_m}^2 + z(t)^2}\Big) - 0.5\,\rho A_w C_d \lvert\dot{z}(t)\rvert \dot{z}(t)\Big] \quad (2)$$

$$x(t) = \left[z(t)\dot{z}(t)q_r(t)^T{}_{1*4}\right]^T \quad (3)$$

$$\dot{X}(t) = Ax(t) + B(f_{ex} + f_u) + \theta \quad (4)$$

$$Y = Cx(t)\; F_{int} = f_{ex} + f_u$$
$$x_1 = z(t) x_2 = \dot{z}(t) x_3 = q_r(t)^T{}_{1*4} \quad (5)$$

The above equations are rewritten in the form of the state space as follows:

$$\dot{x_1}(t) = \dot{z}(t) = x_2$$
$$\dot{x_2}(t) = \ddot{z}(t) = \frac{1}{m+m_\infty}\Big[f_{ex} + f_u - C_r x_3 - (s_b + s_{rs})x_1 - R_{loss}x_2 - 2S_m x_1\Big(1 - l_m\sqrt{{l_m}^2 + {x_1}^2}\Big) - 0.5\,\rho A_w C_d \lvert x_2\rvert x_2\Big] \quad (6)$$
$$\dot{x_3}(t) = A_r x_3 + B_r x_2$$
$$y = x_2$$

Moreover, the state space matrix is obtained as follows:

$$\begin{bmatrix}\dot{x_1}(t)\\ \dot{x_2}(t)\\ \dot{x_3}(t)\end{bmatrix} = \begin{bmatrix}0 & 1 & 0_{1*4}\\ -\frac{S_b+S_{rs}}{m+m_\infty} & -\frac{R_{loss}}{m+m_\infty} & -\frac{C_r}{m+m_\infty}\\ 0 & A_r & B_r\end{bmatrix}\begin{bmatrix}x_1(t)\\ x_2(t)\\ x_3(t)\end{bmatrix} + \begin{bmatrix}0\\ \frac{1}{m+m_\infty}\\ 0\end{bmatrix}F_{int} + \begin{bmatrix}0\\ \frac{-2S_m x_1\left(1 - l_m\sqrt{{l_m}^2 + {x_1}^2}\right) - 0.5\,\rho A_w C_d \lvert x_2\rvert x_2}{m+m_\infty}\\ 0_{1*4}\end{bmatrix} \quad (7)$$
$$y = [0 \quad 1 \quad 0]\begin{bmatrix}x_1(t)\\ x_2(t)\\ x_3(t)\end{bmatrix}$$

According to Eq. (4), the system has two inputs. The first input is the control force applied by the PTO, i.e., the PMLG; this force, which is denoted by $f_u(t)$, can be designed and modified to maximize the power generation. The second input is the wave excitation force, $f_{ex}(t)$, which is defined as a disturbance and cannot be designed and modified. For simplicity, the existing system is converted into a single-input single-output system, so these two forces are incorporated [3]. The power output of the system and the absorbed energy of the WEC in the interval $[T_1، T_2]$ are expressed as follows:

$$P(t) = -f_u.\dot{z}(t) \quad (8)$$

$$E = \int_{T_1}^{T_2} P(t) \quad (9)$$

The Bretschneider spectrum is one of the most important and practical spectral wave forecasting methods. The irregular Bretschneider wave spectrum is introduced using the nonlinear model of point absorber converters. Due to the

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unpredictable and irregular behavior of the waves, in order to match the exact irregular waves with a floating body, the linear and nonlinear forces that act on a converter have to be included to extract maximum power. To simulate WEC behavior, it is necessary to feed the model with an input wave. The Bretschneider spectrum is considered with two parameters to produce random waves. The chosen parameters of spectrum S(ω) are a combination of the wave height Hs and the energy period Te [13].

$$S(\omega) = \frac{5\omega_m^4}{16\omega^5} H_s^2 e^{-5\omega_m^4/4\omega^4} \tag{10}$$

We consider ±30% uncertainties in nominal parameters in the nonlinear model. In order to model these uncertainties, a fuzzy controller is designed and is then optimized using an intelligent optimization method. This control strategy is explained in section 4. In order to validate the proposed method, simulations are performed in section 5 to show that the proposed method can overcome uncertain conditions.

4. Control Strategy

The technologies related to ocean energy exploitation is less evolved in comparison to technologies of other existing energies and need to overcome a wide range of engineering challenges to resolve future problems. As a result, we outline here the main challenges in the field of ocean energy technology. Many parameters affect the power generation of WECs, so their optimization at the design or power generation stages requires a dynamic control, which results in maximum power output. Controllers work at different time or frequency scales, and their accurate performance depends on the precise measurement of system parameters.

A) Fuzzy controller design

According to Table 2, a fuzzy controller can be an appropriate choice for accurate control of system parameters for the following reasons:

- System depreciation over time and change in spring constant and damping coefficient, which are parameters varying with time.
- The existence of nonstationarity noise in WECs, which behaves completely randomly and unpredictably.
- Different atmospheric conditions in the oceans lead to large uncertainties in the mentioned coefficients.
- Suitable for a variety of seas with different depths.
- Use of fuzzy controllers nearshore and offshore.
- In point absorbers, in the event of a sudden increase in the wave, sensors disable the system in order to prevent damage to the PTO drive; by taking these sudden uncertainties into account, power generation is enhanced.

Different control strategies can be designed for controlling WECs. Some of these strategies are: hydrodynamic control [14] [15], power take-off control [16] [17] and network/load control [18] [19]. Each of these strategies correspond to a specific part of the system. In this paper, a control strategy is proposed for a PTO system. This strategy affects the basic recording system, electrical equipment and performance of the PTO. The PTO control systems are classified into reactive and resistive controls [20]. The mathematical model of the PTO system is given as follows:

$$f_{pto} = f_{\mathrm{u}} = -R_U \dot{Z}(t) + S_U Z(t) \tag{11}$$

where S_{u} is the spring constant and R_{u} is the damping coefficient; by tuning and controlling these parameters, the phase and amplitude of the WEC motion can be modified. This results in more power generation in the system. The input force $f_{\mathrm{u}}(t)$ is the same as the force under control, which is exerted by the PTO on the converter. Here, the limitations of the PTO system are considered in the fuzzy control system, and the parameters R_U and S_U are calculated with respect to the fuzzy controller. According to the block diagram of a fuzzy control system [21], the control block diagram in this paper is considered to have error and error derivative as the inputs as well as spring constant and damping coefficient as the outputs:

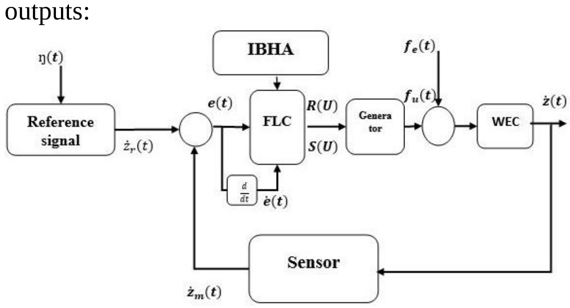

Fig. 5. Block diagram of a fuzzy control system optimized with BHA.

In Fig. 5, it can be seen that forces fu and fex are exerted on buoy WEC. Besides the fuzzy controller parameters, five other coefficients are considered. Two coefficients corresponding to the fuzzy inputs are the error and its derivative. Coefficients R(U) and S(U) correspond to the fuzzy outputs; finally, the last coefficient is related to fex. These five coefficients are adjusted by the proposed black hole optimization algorithm. A total of 61 control parameters are adjusted by the proposed algorithm.

B) Fuzzy controller optimization based on black hole algorithm

This new meta-heuristic algorithm is inspired by the phenomenon of black holes. Similar to other population-based algorithms, the black hole algorithm starts with the initial population of candidate solutions for a problem and optimizes the target function for which it is computed. Its performance in achieving global optimization is better than other algorithms. Here, we first consider a primitive population as a solution, which is the initial population of the same consequent and antecedent parameters in Gaussian fuzzy membership functions. For each parameter the fitness is fitted and the best parameter is selected as a black hole. Then, using Eq. (13), the star change is made to find the best solution:

where $x_{\mathrm{i}}(\mathrm{t})$ and $x_{\mathrm{i}}(\mathrm{t}+1)$ are the locations of star i at iterations t and t + 1; $\mathrm{x_{BH}}$is the location of the black hole in the space.

Eventually, if a star is to the event horizon $R = \frac{f_{BH}}{\sum_{i=1}^{N} f_i}$where $f_{BH}$is the fitting of the black hole and $f_i$is the value of the fit of the star i and N of the number of stars (the candidate solution). That star will be deleted and instead a new star will be randomly searched in the space.

The ending criterion will be the best fit, and for each of these answers we calculate the fitness function as follows:

$$e = \dot{z}_r(\mathrm{t}) - \dot{z}(t)$$
$$\min(\mathrm{ITAE}) = \min(\int_0^{t_f} t|e(t)|) \quad (12)$$

This indicator can be used for variable time error or absolute error rate known as ITAE or ITFA

C) Improved chaos-based black hole algorithm

The limitations of the black hole algorithm are random parameters and population, as well as weak exploration and exploitation. The random parameters of black hole algorithm may affect the performance of the algorithm and cannot guarantee global coverage to the entire search space. As a result, the accuracy and speed are relatively low. The combination of chaos and black hole algorithm improves the accuracy and speed of the optimal response.

In the population cycle, some conditions are first considered. If a random number is greater than 0.6, xi (t+1) is calculated from Eq. (13). However, for a random number greater than 0.5, we have:

$$x_i(t+1) = x_i(t) + 2rand(x_{BH} - x_i(t)) + 20w * rand(n) \quad (13)$$

where w is the inertia coefficient. This coefficient starts at a large value and then decreases linearly. In each iteration, the inertia coefficient varies according to Eq. (14).

$$w = w * w_{damp} \quad (14)$$

where w_{damp} is the damping coefficient and is equal to 0.75. In the second term of equation (13), the inertia coefficient is multiplied by a normally distributed random number (randn), so global search is considered first. Then, as the inertia coefficient decreases, the exploitation is considered. From now on, the inertia coefficient is used in equations.

For a random number greater than 0.2:

$$x_i(t+1) = x_i(t) + 2w * rand(x_{BH} - x_i(t)) + 20w * rand(n) \quad (15)$$

Here, the weight factor w is inserted into the term describing the motion towards black hole, and by increasing the number of iterations, the speed of the motion is reduced. Moreover, a random normal distribution by a factor of 20 is multiplied by the inertia coefficient and added to the equation. This results in a balance between the global and local search.

However, if the random number is smaller than 0.2, some new conditions are investigated. If the random number is greater than 0.3, a mutation is considered according to Eq. (16):

$$x_i^m(t+1) = x_i^m(t) + 2w * z(t) + 20rand(n) \quad (16)$$

where a member m is randomly selected from the population. In this equation, the current position of the member is obtained from the previous position plus the product of inertia coefficient, the chaotic expression $z(t)$ multiplied by a factor of 20. Actually, the chaotic properties are utilized to make the population more diverse. A normally distributed random number multiplied by 20 is also added to Eq. (17) to result in an even larger mutation. Equation (16) is intended to improve the global search of the algorithm.

The chaotic mapping $z(t)$ used in Eq. (17) is described as follows:

$$z_{j+1} = \lambda z_j (1 - z_j)$$
$$for \quad 0 < \lambda \le 4 \quad j = 0,1,2,... \quad z_j \in [0,1] \quad (17)$$

The mapping shows a chaotic behavior for, if the initial condition $z_0 \neq \{0, 0.25, 0.5, 0.75\}$ hold.

However, for a random number smaller than 0.3, if a member of the population is at a maximum or minimum point of the search range, the parameter is moved away from the maximum or minimum point using a specific term. If the parameter is equal to the minimum range, the following equation is executed:

$$x_i^m(t+1) = x_i^m(t) + 50z_1(t) \quad (18)$$

where m is a parameter of the ith member, which is in the minimum search range.

If the parameter is within the maximum search range, the following equation is executed:

$$x_i^m(t+1) = x_i^m(t) - 50z_1(t) \quad (19)$$

This equation results in the maximum distance of the parameter that is within the maximum search point.

5. Simulation

A) Simulation results of improved black hole algorithm for benchmark functions

The results of implementing the proposed improved black hole algorithm on several benchmark functions are presented in this section. The employed benchmark functions include Sphere, Rosenbrock, Rastrigin, Zakharov, Schwef and a combination of three functions Elliptic, Schwefel and rastrigin, as mentioned by Liang and Suganthan in 2014 (J.J. Liang1, 2013). For evaluating the performance of the proposed algorithm, its results are compared to the conventional black hole and particle swarm optimization algorithms.
The parameters of the algorithms are adjusted as follows. The maximum number of iterations is 100, and the population size is considered to be 70. Simulations are performed 30 times for each algorithm. The results are presented in Tables 5 and 6.

Table.5.
Comparison of simulation times and standard deviations obtained from the IBH, PSO and conventional BH algorithms using benchmark functions.

	Time BH	Time IBH	Time PSO	Std BH	Std IBH	Std PSO
Sphere	3.8937	4.3656	1.5441	1.14e-05	3.79e-08	3.5286
Rosenbrock	3.4951	4.0711	1.4716	64.394	25.767	534.45
Rastrigin	19.888	3.7877	1.2466	16.678	4.4847	39.605
Zakharov	7.3671	3.6289	1.2117	59.979	0.10322	56.283
Schwef	9.0284	3.3871	1.146	216.43	6.54e-08	0.8877
Hybrid	16.937	2.9392	1.1689	4.25e+06	2.4397	75584

Table.6.
Comparison of the best values of cost function and their means obtained from the IBH, PSO and conventional BH algorithms using benchmark functions.

	Mean BHA	Mean IBHA	Mean PSO	Min BHA	Min IBHA	Min PSO
Sphere	4.46e-06	1.54e-08	4.7603	1.6e-09	8.1e-11	1.2249
Rosenbrock	47.617	12.891	805.9	0.7683	0.2830	280.38
Rastrigin	26.923	14.045	144.02	7.9602	6.0062	85.431
Zakharov	29.728	0.07624	109.29	0.1107	9.27e-05	40.822
Schwef	134.42	6.95e-08	1.1669	2.26e-07	3.95e-10	0.33778
Hybrid	2.118e06	1.2279	2.03e05	404.03	5.12e-05	66505

According to Tables 5 and 6, it is clear that the proposed algorithm has the best mean and standard deviation of obtained costs, as well as the minimum cost function, compared to PSO and conventional BH algorithms. The simulation of PSO algorithm takes less time because of simpler structure of the algorithm. However, there is no significant difference between simulation times of the IBH and PSO algorithms. According to the obtained results, it is concluded that the proposed BH algorithm is successful in minimizing benchmark functions. In the next section, this algorithm is used to tune the fuzzy controller parameters and coefficients.

B) Tuning of fuzzy logic controller parameters using IBHA results

The technologies related to ocean energy exploitation is less evolved in comparison to technologies of other existing energies, and it is necessary to overcome a wide range of engineering challenges before investing much money in these technologies. Accordingly, this subsection outlines the main challenges facing innovation in the field of ocean energy exploitation technologies.
According to Eq. (10), parameters ω_s and H_s are selected by the designer and can be varied under different conditions of the sea. Figure 6 shows the Bretschneider spectrum as the input to the WEC system.

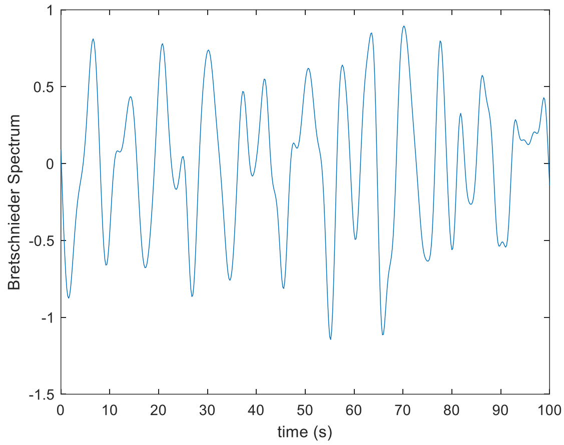

Fig. 6. The Bretschneider spectrum

After calculating the input wave spectrum, the wave excitation force is obtained. According to Table 4, the wave excitation force can be calculated using the convolution of wave height and impulse response function k_{ex}. Indeed, the value of k_{ex} can be obtained by using the second or fifth order approximation of an exponential function using MATLAB curve fitting tool and Digitizer software.
Figures 7 and 8 show, respectively, the impulse response function and wave excitation force.

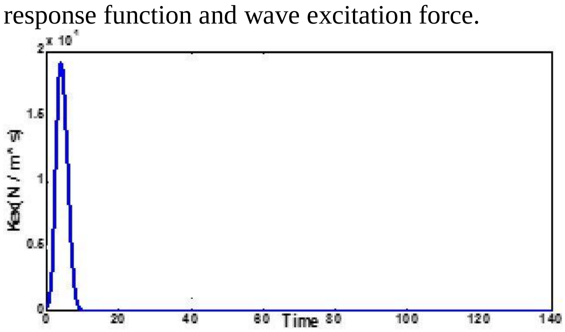

Fig. 7. Fifth order approximation of excitation force impulse response function.

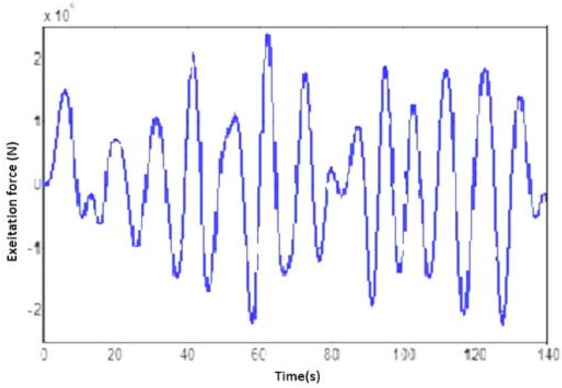

Fig. 8. Wave excitation force

Until the controller is not applied to the system, the wave excitation force acts on the point absorber. In this case, as shown in Fig. 9, the velocity of the floater ($\dot{z}$) and the input wave velocity ($\dot{z_r}$) are not in phase before the controller is applied, and the output does not track the reference signal.

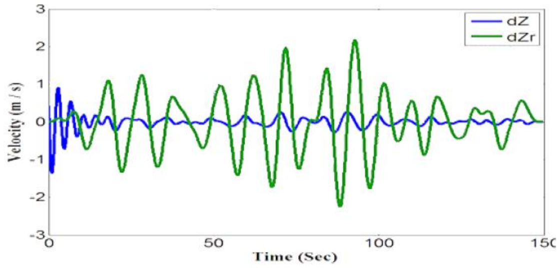

Fig. 9. Input waves and velocity of the floater without control.er

In this situation, we consider an error input, an error derivative and seven membership functions for each input, so FIRING order is equal to 7. To optimize the parameters of the membership functions, it should be noted that each Gaussian membership function has two parameters. Therefore, for the 14 membership functions, there are 28 parameters in total that should be optimized using the chaotic black hole optimization algorithm; i.e., the membership parameters (stars) change to approach the black hole, and this process of approaching is conducted by the rand operator.

The ranges of control parameters are as follows: damping coefficient is in the range of 0-105, and the spring constant is in the range of 0.1-2; error ranges from -5 to +5, and the error derivative ranges from -1 to 1.

Because of the uncertain frequencies in the model, two coefficients can be considered for two fuzzy controller outputs so that their values can be adjusted using the optimization algorithm to improve the cost function of the problem.

The coefficients K1 and K2 are considered to be in the range [0.01, 2], so RU and SU ranges are also improved.

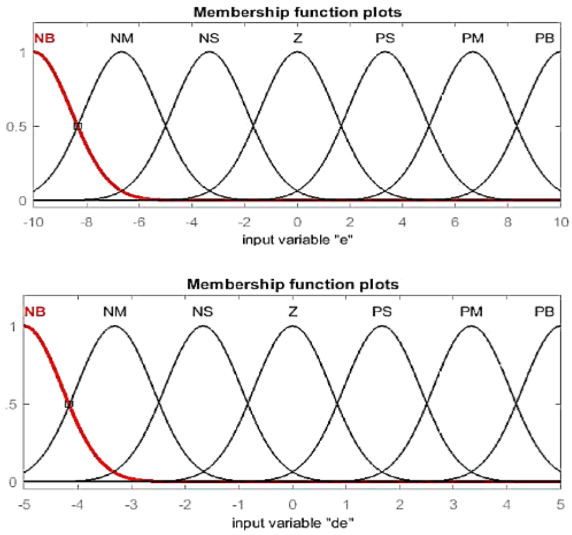

Fig. 10. The controller's membership functions related to error inputs and error derivatives before optimization

After optimizing the membership parameters using the improved black hole algorithm, error inputs and error derivatives are set as follows:

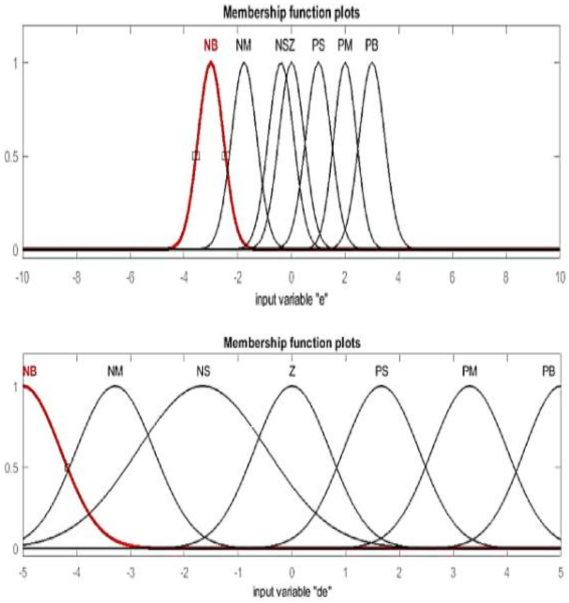

Fig. 11. Set parameters of membership functions using chaotic black hole algorithm

According to Fig. 12, it can be seen that the improved fuzzy controller method with the chaotic black hole algorithm has been able to track the reference speed faster and better than the BHA and PSO fuzzy controller methods. It is evident from the figure that the error resulted from the conventional fuzzy controller is higher than the proposed method. The efficiency and validity of the proposed method is proved.

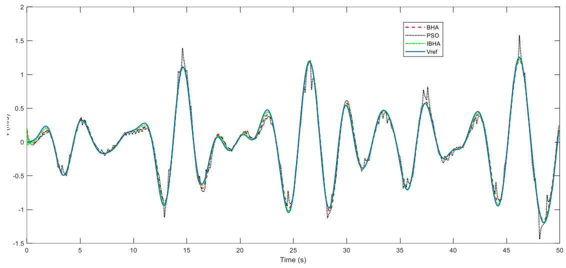

Fig. 12. Wave velocity curve and comparison of reference velocity with conventional fuzzy controller and fuzzy controller improved using chaotic black hole algorithm.

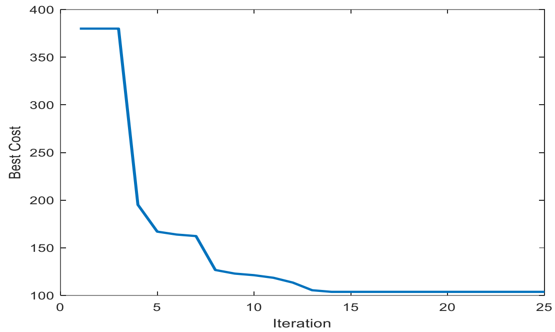

Fig. 13. Cost function for 25 iterations.

In Fig. 13, the best value of the cost function is 103.7747 at iteration 25, and mse = 0.0011. It is seen in Fig. 14 that the value of control effort for the fuzzy controller is improved using the proposed black hole algorithm compared to PSO and BH fuzzy controllers.

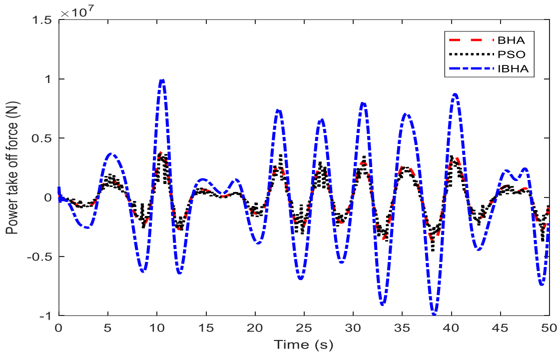

Fig. 14. Control efforts made by the fuzzy controller tuned by BH, PSO and IBH algorithms.

Figures (15) and (16) show, respectively, the power and energy absorbed by the WEC. From Figs. 15 and 16, it can be observed that power generation has increased considerably in the proposed method compared to fuzzy controller with BH and PSO algorithm.

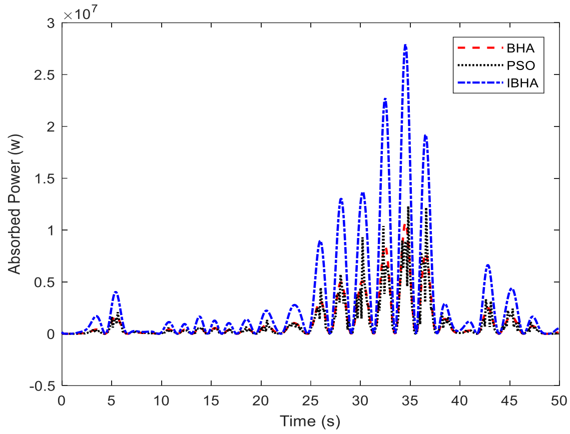

Fig. 15. Comparison of power generated using fuzzy controller adjusted by BH, PSO and IBH algorithms.

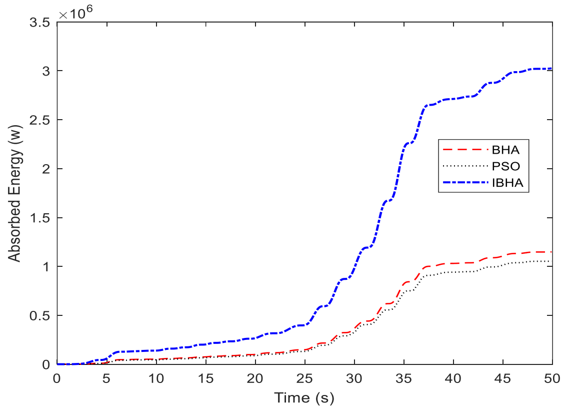

Fig. 16. Total energy obtained using fuzzy controller adjusted by BHA, PSO and IBHA.

6. Conclusion

The main purpose of this paper was to analyze power generation by ocean waves. The system under study was simulated and evaluated using a fuzzy logic controller. This controller was intended to tune the parameters of the WEC system in order to maximize the power output of the converter. The Fuzzy controller that was optimized by the IBH-FLC algorithm was operated in different atmospheric conditions, and its performance was compared to other optimization methods, such as PSO and convention black hole algorithms. In general, with a change in the reference speed, the proposed fuzzy controller can adapt itself to different reference speeds and is more robust, while the conventional fuzzy controller is inefficient in speed tracking and power generation.

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