Renewable Energy 63 (2014) 109–115

Contents lists available at ScienceDirect

Renewable Energy

journal homepage: www.elsevier.com/locate/renene

Offshore wind farm design with the Coral Reefs Optimization algorithm

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ARTICLE INFO

Article history:
Received 21 February 2013
Accepted 3 September 2013
Available online

Keywords:
Offshore wind farm
Design and optimization
Coral Reefs Optimization algorithm

ABSTRACT

This paper presents a novel algorithm for wind farm design and layout optimization: the Coral Reefs Optimization algorithm (CRO). The CRO is a novel bio-inspired approach, based on the simulation of reef formation and coral reproduction. The CRO is fully described and detailed in this paper, and then applied to the design of a real offshore wind farm in northern Europe. It is shown that the CRO outperforms the results of alternative algorithms in this problem, such as Evolutionary Approaches, Differential Evolution or Harmony Search algorithms.

1. Introduction

Wind power is one of the most promising renewable energy sources in the world [1,2], pushed by the crisis of fossil fuels and the environmental concerns that their excessive use produce. Wind power installed worldwide by the end of 2011 reaches a total of 238 GW, of which about 62 GW correspond to China, 47 GW to USA, 29 GW to Germany, 21 GW to Spain and 16 GW to India [3]. Wind power penetration is rising year by year in many countries, reaching a remarkable 26% in Denmark, 16% in Spain and Portugal, 12% in Ireland, and 9% in Germany [4]. Wind energy penetration in other developed countries is smaller (USA 3.3% [5], Italy 4.2% or France 2.8% [4]), though it is known that these figures will increase a lot in the next few years.

Wind energy is mainly produced in large production facilities called *wind farms*. In the past five years, new wind energy production facilities in the world have grown about 25% each year, and the forecast for 2013 is that the annual growth rate still remains a remarkable 15%. The majority of wind farms are located in land (onshore facilities), but wind farms located in the sea (offshore) seem to be more productive, and many companies are betting on this kind of facility when geographical conditions allow its installation. In fact, recent studies have reported a significant increment in the installation of offshore wind farms over 30% with respect of previous years [6]. In Europe, these facilities have been installed for more than 20 years ago, and nowadays represent a significant part of wind energy production in countries such as Denmark, Sweden or the Netherlands [7]. In addition, other studies have shown that the potential of offshore wind energy in important economies such as China [8] or Europe [9] is much larger than its onshore counterpart. Following recent studies [7], the main advantages of offshore wind farms are the availability of huge continuous areas for developing major projects, the higher wind speeds at the sea, less effects of turbulence or the elimination of visual impact and noise issues, among others. On the other hand, there are also several disadvantages with these facilities, such as more expensive installation and connection to the electrical network or limited access for maintenance operations, etc.

The increasing number of projects focussed on the installation of new wind energy facilities, has had an immediate effect in the research about wind farms' design. Moreover, automatic wind farm design based on optimization algorithms is nowadays a hot topic in wind energy, with dozens of articles and research works published recently. In fact, the pioneering work on automatic wind farm design is due to Mosetti et al. [10], back in the 1990's. In that paper, a genetic algorithm was proposed to tackle the problem of the optimal turbines layout in a wind farm. The model proposed in Ref. [10] has served as inspiration to many other articles, for example, the works by Grady et al. [11] or Emami et al. [12], that proposed different improvements in the objective function and genetic operators to obtain better search capabilities in the algorithms. Also

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http://dx.doi.org/10.1016/j.renene.2013.09.004

dealing with evolutionary algorithms, the work by Mora et al. [13] describes a variable-length genetic algorithm with novel procedures of crossover, that are very effective to obtain optimal wind turbines layouts, including monetary cost as the objective optimization function. A similar approach using a hybrid evolutionary algorithm was previously presented in Martínez et al. [14]. This approach has been further studied recently in Refs. [15,16]. It is also significant the work by Sisbot et al. [17], that proposed a multi-objective evolutionary algorithm for a specific problem of wind farm design in Turkey, and the works by Wang et al. [18], where new improved wind and turbine models have been considered within a genetic algorithm. Another work that deserves special consideration is the one by Kusiak et al. [19], where a complete study of the problem including very different aspects and assumptions is considered. The authors solve the problem by applying an evolutionary programming approach. Other important works have been recently proposed based on evolutionary algorithms, such as the one by Wan et al. [20] where a real-coded genetic algorithm is proposed, the work by Huang [21] based on hybrid genetic algorithms, or the work by Saavedra et al. [22], where an evolutionary approach that considers wind farm shape and orography is proposed. There are also other bio-inspired approaches (alternative to evolutionary algorithms), that have been successfully applied to the wind farm design problem, for example the paper by Wan et al. on Particle Swarm Optimization [23] and the work by Eroglu et al. based on Ant Colony Optimization [24]. An excellent review of the most significant papers focus on onshore wind farm design has been recently published by Khan and Rehman [25].

There are also other works specifically focused on the optimal design of offshore wind farms using bio-inspired techniques. For instance the works by Elkinton et al. [26–28], where a novel model for the design of offshore wind farms is presented, and several approaches were compared in this problem. A greedy algorithm, a genetic algorithm, a pattern search approach and a simulated annealing techniques were tested in this problem. The work by Rivas et al. in Refs. [29], is also relevant. In that paper the authors proposed a simulated annealing algorithm to solve a problem of optimal turbine sitting in offshore wind farms. In the work by Zhao et al. [30] the authors presented a different approach for offshore wind farm design, focussed on minimizing the connections between wind turbines, considering a fixed layout of turbines. Finally, in a quite recent paper by Pérez et al. [31], the authors have proposed a specific approach to a problem of offshore wind farm design, based on mathematical programming techniques, specifically a combination of heuristic and gradient-based algorithms, that provides a good solution to the design of a real wind farm in northern Europe.

This paper is focussed on offshore wind farm design with a new optimization technique, the Coral Reef Optimization (CRO) algorithm. The CRO is a novel bio-inspired meta-heuristic for optimization problems, based on an artificial simulation of the coral reefs' formation and reproduction processes. The CRO algorithm emulates different phases of coral reproduction and fight for space in the reef, and finally produces an efficient algorithm for solving difficult optimization problems. The proposed CRO approach can be seen as a cellular-type evolutionary scheme, with superior exploration–exploitation properties thanks to the particularities of the emulated reef structure and coral reproduction. In this work we test the performance of the CRO in the design of an offshore wind farm in northern Europe, comparing its performance with that of alternative existing bio-inspired approaches. The results obtained show that the CRO is a competitive algorithm to be considered in optimization energy-related problems.

The rest of this article is structured as follows: the next section presents the CRO algorithm in detail, including an introduction to reefs and corals' structure and reproduction and an analysis of similarities and differences with other existing meta-heuristic algorithms. Section 3 shows the performance of the CRO algorithm in the design of an offshore wind farm. Finally, Section 4 ends the paper by giving some concluding remarks.

2. The Coral Reef Optimization algorithm (CRO)

This section describes some important properties of corals and coral reefs that will be simulated by the CRO approach. In order to introduce the algorithm, some characteristics of corals and reefs are provided. Details on the CRO implementation are provided at the end of the section.

2.1. Corals and reef formation

A coral is an invertebrate animal belonging to the group *phylum-cnidaria*, which also includes sea anemones, hydras or jellyfishes [32]. In fact, a more detailed classification includes corals in the *Anthozoa* class, together with sea anemones, sea pens or sea pansies. These animals are characterized by their ability to subsist either as individuals or in colonies of polyps, living attached to a substrate. There are more than 2500 different species of corals, living in shallow and deep waters, and each year new species are found and described.

An important subclass of corals are reef-building corals, also known as *hermatypic* or simply *hard corals*. Hard corals are usually shallow-water animals that produce a rigid skeleton of calcium carbonate, segregated from their base. A coral reef is formed by hundred of hard corals, cemented together by the calcium carbonate they produce. Periodically, the polyp lifts off its basal plate of calcium carbonate and secrete a new one, forming a tiny chamber that will contribute to the coral's skeleton. All polyps in the reef build and add these chambers to the reef, so the reef will grow upwards. Living corals grow on top of the skeletons of calcium carbonate of their dead predecessors. A coral reef is usually formed by corals living in colonies, or on its own. A colony is composed of a single specie of coral, but a reef's structure can comprise multiple types of species. In fact, a coral reef finally ends up as a true ecosystem, in which a diverse collection of animals and plants interact with each other, as well as with their environment. In addition to corals, many other animals and plants live in and from the reef, such as algae, sponges, sea anemones, bryozoans, sea stars, crustaceans (e.g. shrimps, crabs, lobsters), octopuses, squids, clams, snails and other mollusca. And, of course, a huge variety of fishes that find shelter and food in the reef.

In general, hard coral species require little space to settle and grow. Although a priori the implementation of this settlement procedure might be easy for a potential new member of the reef, in practice free space is an extremely limited resource in the reef environment [33]. As a result, species often compete with each other or exhibit aggressive behavior to secure or maintain a given plot of substrate [34]. Different strategies used by corals to compete for the space have been thoroughly described in the literature [34,35]. Among them, fast-growing is deemed as the most used and simple strategy since it grounds on the fact that there are corals that have evolved to yield a faster growth rate than others. When a fast-growing coral sets near a slow-growing one, the former attacks the latter by overtopping it. The underlying coral suffers from light deficiency, thus affecting its ability to conduct photosynthesis and to get into contact with food particles. As time evolves, overtopping by fast-growing species kills the slower-growing species underneath. Other aggressive strategies carried out by some species of corals include sweeper tentacles (i.e. detect and damage adjacent coral colonies), *mesenterial* filaments (namely, enabling external digestion of neighboring colonies), and *terpenoid compounds* (coral chemical warfare).

2.2. Coral reproduction

Corals can reproduce in two different modes: sexual or asexual. In fact, an individual polyp may use both modes within its life time [32]. Furthermore, sexual reproduction can be either external or internal, depending on the coral species.

2.2.1. Sexual external reproduction: broadcast spawning

The majority of hard corals species resort to a sexual external reproduction method known as *broadcast spawning* [36]: every coral produces male and/or female (some species of corals are hermaphrodites) gametes that are massively released out to the water. Once the egg and sperm meet together, a larva (also called *planula*) is produced. Planulae float in the water until they find a proper space to attach and start growing a polyp [37]. In the majority of reefs, the phenomenon of coral spawning occurs as a synchronized event. This timing is crucial for successful reproduction, since corals can not move to force reproductive encounters. There are different natural aspects that affect the timing of the corals' spawning, such as temperature, day length or temperature change rate.

2.2.2. Sexual internal reproduction: brooding

Brooding is a method of internal reproduction used by some species of corals. In this reproduction mode, some female polyps contain eggs that are not released to the water. Instead, sperm released by other male corals of the same species gets inside the polyp and fertilizes the eggs, producing small planulae. These planulae are released later through the mouth of the coral in an advanced stage of development, so it becomes easier for these planulae to set onto hard substrate without being attacked or depredated. There has also been described a type of brooding reproduction in hermaphrodite corals [38].

2.2.3. Asexual reproduction: budding or fragmentation

Budding is a form of asexual reproduction in corals: basically, new polyps bud off from parent polyps to expand or begin new coral colonies [39]. Budding occurs when the coral has grown enough to produce budding. Fragmentation is a process similar to budding, but it is caused by external phenomena (e.g. storms or boats' grounding), and usually a larger part of the coral is divided in comparison to budding [40]. As such, in fragmentation a part of a coral colony is separated from the parent polyps. Individuals broken off this way from the main colony are able to keep growing and finally establishing a new colony far way from the parent one if conditions are favorable. It is important to note that both budding and fragmentation processes produce polyps that are genetically identical to the parent polyp/colony.

2.3. Reef longevity and causes of death

There are not reliable statistics on corals' lifespan. However, it is well known that coral colonies can live for several centuries. Corals and coral reefs must face different hazards during their life. In larva state, corals are massively depredated by fishes and other predators. However, the huge number of larvae produced in broadcast spawning reproduction ensures that enough polyps settle in favorable ground and start forming a colony. On the other hand, coral polyps encounter many types of predators including sea stars, parrot-fishes or butterfly-fishes. Human activities (e.g. fishing activities, or industrial processes that increase ocean pollution) and climate changes (increase of the oceans' temperature, among others) also contribute to the loss of living corals [41].

2.4. CRO implementation

Having these fundamentals on the corals' reproduction and formation in mind, the CRO algorithm tackles optimization problems by modeling and simulating all the distinct processes explained in the above Section 2. Let Λ be a model of reef, consisting of a $N \times M$ square grid. We assume that each square (i,j) of Λ is able to allocate a coral (or colony of corals) $\Xi_{i,j}$, representing different solutions to our problem, encoded as strings of numbers in a given alphabet $\mathcal{I}$. The CRO algorithm is first initialized at random by assigning some squares in Λ to be occupied by corals (i.e. solutions to the problem) and some other squares in the grid to be empty, i.e. holes in the reef where new corals can freely settle and grow. The rate between free/occupied squares in Λ at the beginning of the algorithm is an important parameter of the CRO

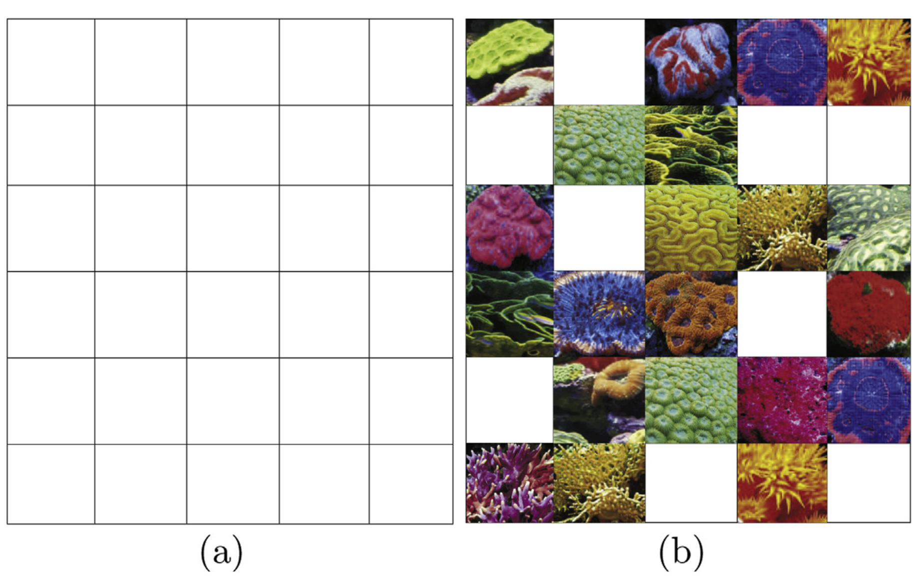

Fig. 1. Coral reef simulation; (a) grid; (b) corals and holes in the reef.

algorithm, which will be denoted in what follows as $0 < \rho_0 < 1$. Fig. 1(a) exemplifies this reef model using a 5×6 grid, whereas Fig. 1(b) illustrates an initialization of the reef with corals and coral colonies representing solutions to a given problem. Note that in this example $\rho_0 = 9/21 \approx 0.43$. Each coral is labeled with an associated *health* function $f(\Xi_{ij}): \mathcal{I} \rightarrow \mathbb{R}$, that represents the problem's objective function. Note that the reef will progress as long as healthier (stronger) corals (which represent better solutions to the problem at hand) survive, while less healthy corals perish.

After the reef initialization described above, a second phase of reef formation is carried out by the CRO algorithm. To this end, a simulation of the corals' reproduction in the reef is done by sequentially applying different operators. This sequential set of operators is then applied iteratively until a given stop criteria is met. Thus, we define different operators for modeling sexual reproduction (broadcast spawning and brooding), asexual reproduction (budding), and polyps depredation. In both sexual and asexual reproduction we give the conditions under which new corals effectively get attached to the reef, or are depredated while at the larvae phase:

1. **Broadcast Spawning (external sexual reproduction)**: the modeling of coral reproduction by *broadcast spawning* consists of the following steps:
   1.a In a given step k of the reef formation phase, select uniformly at random a fraction of the existing corals ρ_k in the reef to be broadcast spawners. The fraction of broadcast spawners with respect to the overall amount of existing corals in the reef will be denoted as F_b. Corals that are not selected to be broadcast spawners (i.e. $1-F_b$) will reproduce by brooding later on, in the algorithm.
   1.b Select couples out of the pool of broadcast spawner corals in step k. Each of such couples will form a coral larva by sexual crossover, which is then released out to the water. Note that, once two corals have been selected to be the parents of a larva, they are not chosen anymore in step k (i.e. two corals are parents only once in a given step). These couple selection can be done uniformly at random or by resorting to any fitness proportionate selection approach (e.g. roulette wheel).
2. **Brooding (internal sexual reproduction):** as previously mentioned, at each step k of the reef formation phase in the CRO algorithm, the fraction of corals that will reproduce by brooding is $1-F_b$. The brooding modeling consists of the formation of a coral larva by means of a random mutation of the brooding-reproductive coral (self-fertilization considering hermaphrodite corals). The produced larva is then released out to the water in a similar fashion than that of the larvae generated in step 1.b.
3. **Larvae setting:** once all the larvae are formed at step k either through broadcast spawning (1.) or by brooding (2.), they will

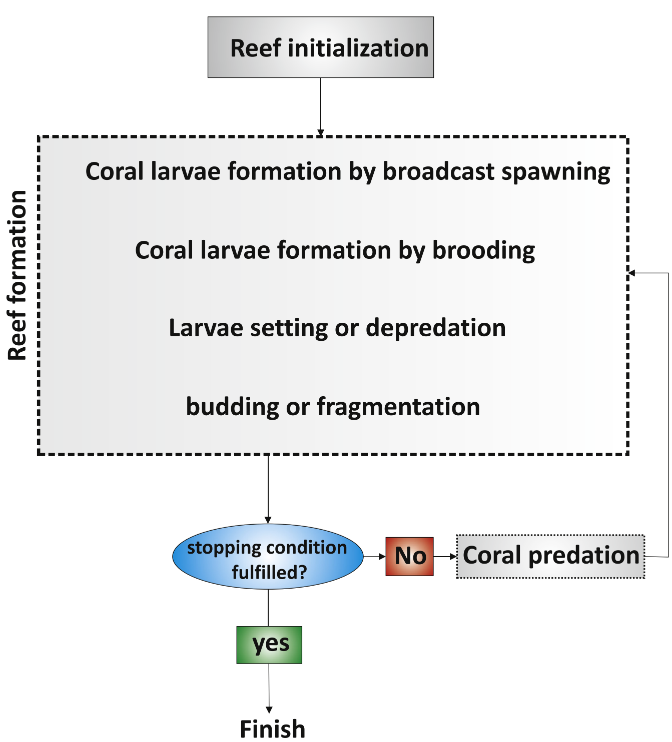

Fig. 2. Flow diagram of the proposed CRO algorithm.

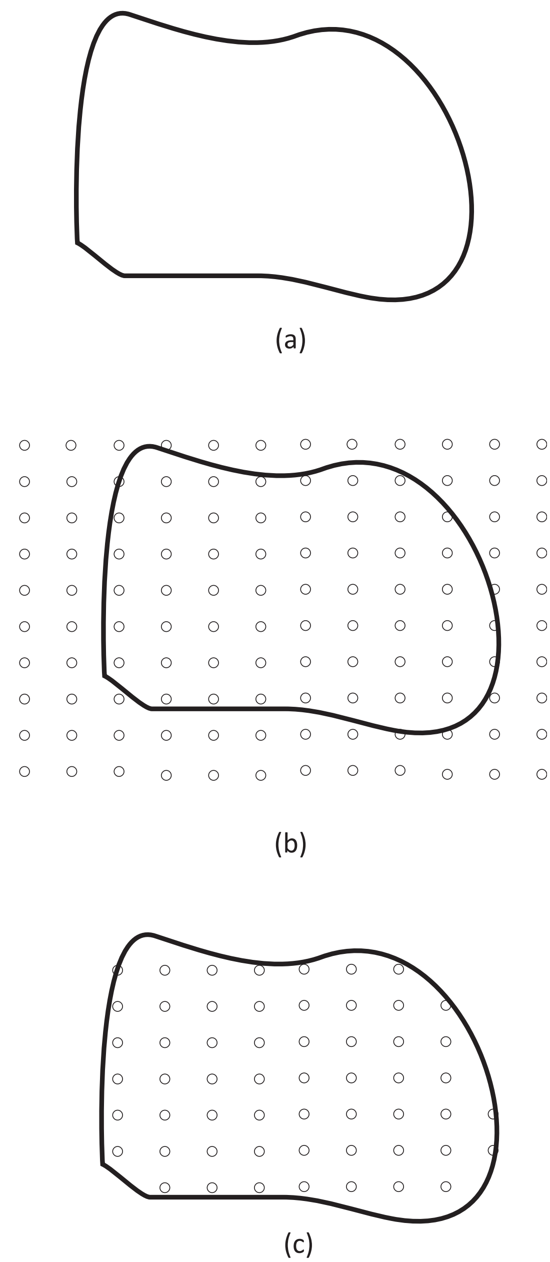

Fig. 3. Example of the problem considered: (a) Wind farm shape (Ω); (b) Regular location points; (c) Points embedded into the wind farm shape (final possible location points to install turbines (Υ)).

try to set and grow in the reef. First, the health function of each coral larva is computed. Second, each larva will randomly try to set in a square (i,j) of the reef. If the square is empty (free space in the reef), the coral grows therein no matter the value of its health function. By contrast, if a coral is already occupying the square at hand, the new larva will set only if its health function is better than that of the existing coral. We define a number κ of attempts for a larva to set in the reef: after κ unsuccessful tries, it will be depredated by animals in the reef.

4. **Asexual reproduction:** in the modeling of asexual reproduction (budding or fragmentation), the overall set of existing corals in the reef are sorted as a function of their level of healthiness (given by $f(\Xi_{ij})$), from which a fraction F_a duplicates itself and tries to settle in a different part of the reef by following the setting process described in Step 3.
5. **Depredation in polyp phase:** corals may die during the reef formation phase of the CRO algorithm. At the end of each reproduction step k, a small number of corals in the reef can be depredated, thus liberating space in the reef for next coral generation. The depredation operator is applied with a very small probability P_d at each step k, and exclusively to a fraction F_d of the worse health corals in Λ. For the sake of simplicity in the parameter setting of the CRO algorithm, the value of this fraction may be set to $F_d = F_a$. Any other assignment may also apply provided that $F_d + F_a \leq 1$ (i.e. no overlap between the asexually reproduced and the depredated coral sets).

Fig. 2 illustrates the flow diagram of the CRO algorithm referencing the two CRO phases (reef initialization and reef formation), along with all the operators described above.

3. Design of offshore wind farms with the CRO

A problem of offshore wind farm design is tackled with the proposed CRO algorithm. To show its performance, a comparison with alternative meta-heuristic approaches is carried out. First, the general problem is stated, and then the specific real case considered is presented. Detail on algorithms parameters are also provided, and the results obtained are finally shown.

Let us consider a wind farm shape Ω, and a grid of possible location points Υ within Ω (see Fig. 3 as an example). It is also considered that the possible location points are separated a minimum security distance of 5D, so all the points in the grid are feasible location to install wind turbines in this case, and no correction is needed. A maximum number of wind turbines N is predefined. The problem consists in obtaining the optimal location of the N wind turbines in the wind farm $S = (x_1,y_1), \ldots, (x_N,y_N)$ in such a way that a measure of the energy production of the wind farm is maximized. Note that S is defined as the best coral in the reef $(\Xi(i,j))$ after the reef formation process defined above. More specifically, we consider the average Annual Energy Production (AEP) of the wind farm, obtained with the fixed N turbines considered in the wind farm Ω, and then define the following health function for the corals in the reef:

$$f(\Xi(i,j)) = \frac{a \cdot \mathrm{AEP}}{\sum_{k=1}^{N} C(k)} \tag{1}$$

where $C(k)$ stands for the cost associated with specific wind turbine k installation (this case considers the possibility that some turbines have different installation costs than others in the wind farm, i.e. some could be harder to be installed than others, due to its location, model, etc.), N is the number of wind turbines installed and a is a normalizing parameter (for comparing the AEP term with $\sum_{k=1}^{N} C(k)$). Note that when the turbine installation cost $C(k)$ is considered equal for all the turbines, i.e. $C(k) = C$, then $\sum_{k=1}^{N} C(k) = C \cdot N$, and Expression (1) is then equivalent to maximize the AEP produced by the evaluated layout $\Xi(i,j)$.

The specific problem tackled in this paper is the design of a real offshore wind farm, located in the Baltic sea. Fig. 4 shows the feasible points of turbine locations and their enveloping silhouette. There are 73 possible locations for turbines in the considered wind

Table 1
Comparison of CRO, EA, DE and HS algorithms in the offshore wind farm design problem.

Algorithm	Energy production (GWh)
CRO	84.352
EA	84.256
DE	84.292
HS	84.284

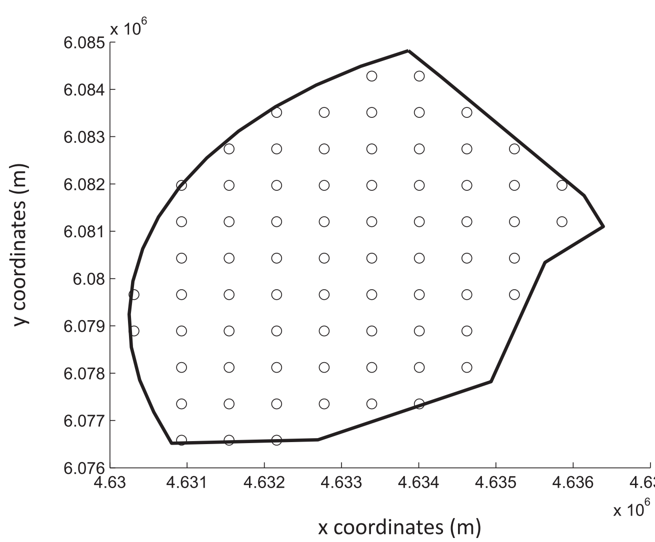

Fig. 4. Real offshore wind farm considered, located in the Baltic Sea, and feasible locations to install wind turbines (in Universal Transverse Mercator (UTM) coordinates).

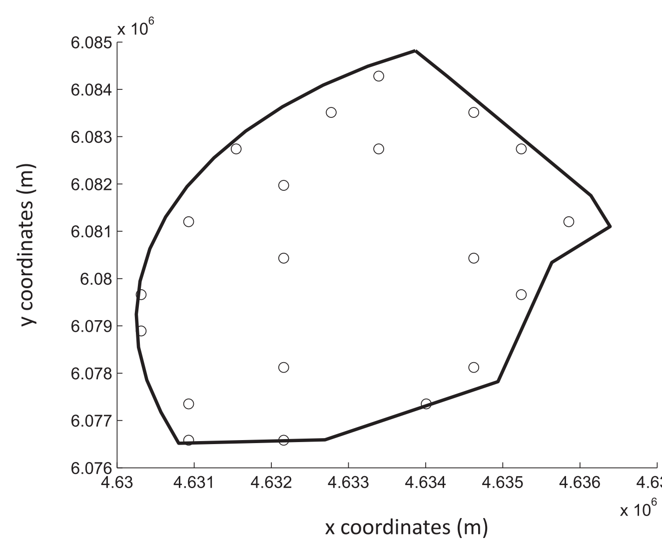

Fig. 5. Best layout obtained by the CRO algorithm (in Universal Transverse Mercator (UTM) coordinates).

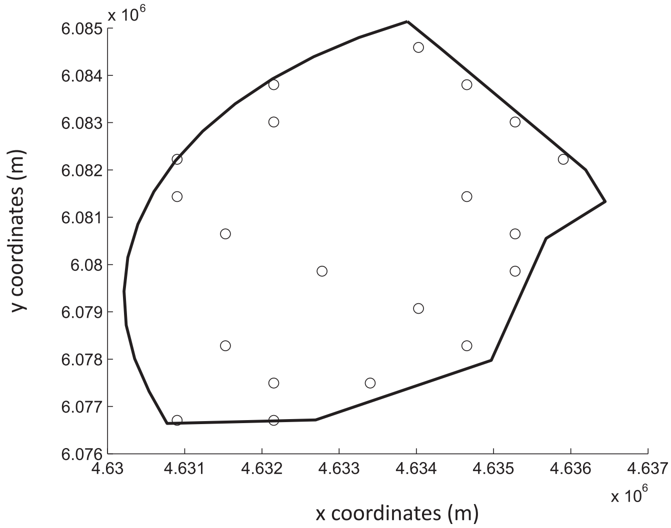

Fig. 6. Best layout obtained by the EA algorithm, the second best approach found in this work (in Universal Transverse Mercator (UTM) coordinates).

farm, and the objective is to install 20 wind turbines in such a way that the production of the wind farm is maximized. The *Bonus* 1.3 MW wind turbine model is considered as the one to be installed in the wind farm, and we suppose an equal installation cost for all then, so the final objective is to maximize the AEP produced by the best coral (layout) found in the reef formation process, *S*. Note that, in this particular case, the well-known *Open Wind* software ([42], freely available) is able to provide a direct calculation of the objective function. Open Wind provides efficient wakes calculation and wind farm production estimation given the wind and terrain characteristics of the wind farm, and the turbine model.

The proposed CRO algorithm's performance has been compared to that of alternative existing meta-heuristics. Specifically, an Evolutionary Algorithm (EA) [43], a Differential Evolution approach [44] and a Harmony Search algorithm [45]. All the compared algorithms use the same encoding approach, i.e. integer numbers between 1 and the maximum number of feasible location sites in the wind farm. The EA includes a population of 50 individuals, with tournament selection, two-point crossover and random mutation

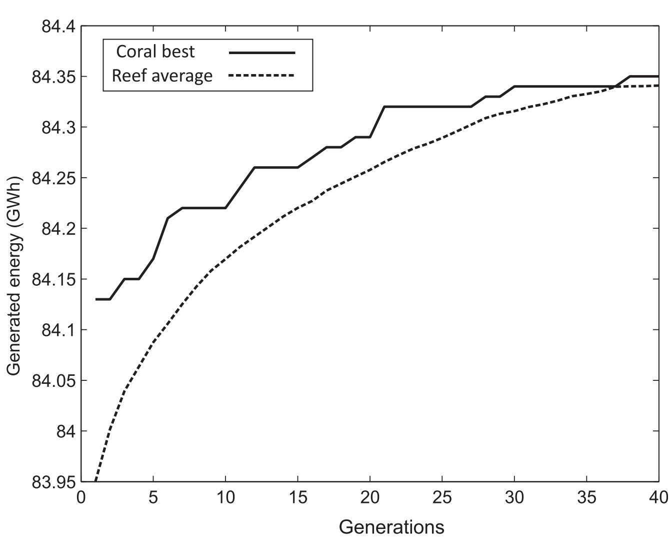

Fig. 7. Evolution of the best solution and average of the reef in the CRO algorithm.

with a probability of 0.1. The chosen DE approach is a classical DE/rand/1/bin, with select weighting factor $F = 0.8$, 50 individuals are also considered in the DE population. The HS algorithm considers a Harmony Memory of 50 harmonies, with parameters (HMCR and PAR) fixed to 0.6. Regarding the CRO approach, a 10×5 reef Λ was considered, with an initial $\rho_0 \simeq 0.7$ and parameter $F_b = 0.9$ (ninety percent of corals are considered as broadcast spawners). All the compared algorithms have been run until the number of objective function evaluations is 3000.

Table 1 compares the best solutions found by the four compared algorithms. Note that the CRO approach produces the layout with the best production, outperforming the EA, DE and HS algorithms, and the differences in favor of the CRO seem significant. Fig. 5 shows the best layout obtained by the CRO approach. Note that the wind turbines location tend to occupy the external-upper zones of the wind farm. The wind rose in the zone of study has a predominant north-west component, and so the solution obtained is logical, since the algorithm tries to locate the maximum number of turbines at the upper left-hand of the wind farm, so these turbines are not affected by wakes disturbances from other turbines. This layout can be compared to the best obtained by an EA (Fig. 6), the second best approach among the four analyzed in this paper. In this layout the turbines also tend to occupy locations at the perimeter of the wind farm, just as in the case of the solution obtained by the CRO approach. However, it seems that, in this case, the solution given by the EA has worse behavior in terms of wake effects than the solution obtained by the CRO approach, so the AEP is affected. Fig. 7 shows the evolution of the CRO (best coral and reef average), where it can be seen the good convergence of the CRO to the best solution found.

4. Conclusions

This paper discuses the performance of a novel bio-inspired approach (the Coral Reefs Optimization algorithm, CRO) in a problem of offshore wind farm design. The paper presents the main characteristics of the algorithm, and different details on its implementation are given. The performance of the proposed CRO algorithm is compared in a real problem of offshore wind farm design with different alternative meta-heuristic algorithms, such as Evolutionary Algorithms, Differential Evolution and Harmony Search, obtaining better results in the problem discussed. The results obtained indicate that the CRO is a good option to solve optimization problems related to energy in an accurate way.

Acknowledgments

This work has been partially supported by Spanish Ministry of Economy, under project number ECO2010-22065-C03-02. This work has also been partially supported by Iberdrola Renovables Energía. L. Carro-Calvo is supported by Fundación Iberdrola through a research fellowship from the program "Programa de Becas y Ayudas a la Investigación 2011-2012 and 2012-2013".

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