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Seeding evolutionary algorithms with heuristics for optimal wind turbines positioning in wind farms

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ABSTRACT

In this paper a novel evolutionary algorithm for optimal positioning of wind turbines in wind farms is proposed. A realistic model for the wind farm is considered in the optimization process, which includes orography, shape of the wind farm, simulation of the wind speed and direction, and costs of installation, connection and road construction among wind turbines. Regarding the solution of the problem, this paper introduces a greedy heuristic algorithm which is able to obtain a reasonable initial solution for the problem. This heuristic is then used to seed the initial population of the evolutionary algorithm, improving its performance. It is shown that the proposed seeded evolutionary approach is able to obtain very good solutions to this problem, which maximize the economical benefit which can be obtained from the wind farm.

1. Introduction

Automatic wind farm design is a topic gaining popularity among wind farm designers and engineers in the last few years. There is an increasing number of articles tackling this problem, successfully applying computational intelligence techniques, mainly evolutionary algorithms, though other approaches have also been used. To start with, a very interesting introduction to the problem, with reference to the wind energy economy and also wind farm designing issues, is given by Swisher et al. in [1]. Also, a recent state of the art in this topic can be found in [2].

The seminal paper in the use of evolutionary computation techniques to wind farm design is the work by Mosetti et al. [3]. This paper proposed a genetic algorithm to tackle the problem of the optimal positioning of turbines in a wind farm. The model proposed in [3] consists in modeling the wind farm as a square divided into cells in which turbines can be situated. A useful wake model was proposed and several experiments considering different average wind speed and direction were presented. This initial work has been the base of different recent approaches which has improved the initial model. For example, in [4] Grady et al. showed that better results can be obtained in the problem by improving the genetic algorithm used, using the same model as in [3]. Another improvement with the same model has been recently proposed by Emami et al. in [5]. This paper proposes a modification of the objective function of the problem, to take into account deployment cost and efficiency of the turbines. The authors show that this modification leads to better design results than previous approaches using a standard genetic algorithm. Another interesting and recent work is the paper by Riquelme et al. [6], where a variable-length genetic algorithm with novel procedures of crossover is applied to solve a problem of optimal positioning of wind turbines, considering monetary cost as the objective optimization function. The authors show that their variable-length evolutionary approach is able to obtain good results in terms of the objective function, considering different types of wind turbines to be used. A similar approach using a hybrid evolutionary algorithm was previously presented in Martínez et al. [7]. This approach has been further studied recently in [8] and [9]. It is also significant the work by Wang et al. [10], where a new improved wind and turbine models have been considered within a genetic algorithm. The authors have shown that this new model is able to produce better results than previous approaches in the literature.

Different computational optimization methods have also been applied to the design of off-shore wind farms, in different works [11–15]. In the works by Elkinton et al. [11–13] a novel model for the design of off-shore 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 technique were tested in this problem. Rivas et al. in [14] used a simulated annealing algorithm to solve a problem of optimal turbine sitting in off-shore wind farms. In [15], Zhao et al. presented

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a different approach to the design of off-shore wind farm design, focussed on minimizing the connections between wind turbines, considering a fixed turbines layout. The authors tested their approach in a real design of an off-shore facility in Liverpool Bay. Three different genetic algorithms were tested, with diverse selection and initialization mechanisms, such as rank-based selection or the niching method. Maybe, the most complete study of wind farm positioning using evolutionary computation up until now is the work by Kusiak et al. [16]. In this work, a complete study of the problem including different cost of turbines and their maintenance, a wind turbine wake model similar to the one described in [3], a Weibull distribution for modeling the wind speed and direction in each point of study is considered. The authors propose then an evolutionary programming approach to solve the continuous optimization problem of optimal positioning of wind turbines using this model. In last few years other approaches to wind farm design, based on evolutionary algorithms and related techniques have been published, such as the works by Wan et al. [17] and [18], based on real-coded genetic algorithms and particle swarm optimization, respectively, the paper by Sisbot et al. [19] based on a multi-objective evolutionary algorithm and the work by Huang [20] based on hybrid genetic algorithms.

Alternative approaches to optimal wind farm design problem, which do not use evolutionary computation, can be found in the literature [21–24]. One of the most interesting works is the one by Marmidis et al. [21], who solved the problem of optimal wind turbines placement using Monte Carlo simulation, and successfully compared the results obtained with that of Grady's genetic algorithm. Also, a very illustrative work is due to Mustakerov et al. [22]. In this paper, the authors model the problem as an integer nonlinear combinatorial optimization problem. Though the authors do not consider real statistics of the wind, the results obtained in two tests with uniform and predominant wind directions in a square and rectangular shape wind farm are quite intuitive and applicable. In Ozturk et al. [24], the authors propose a number of heuristic to come up with a feasible and fast solution to a problem of wind turbine positioning. Finally, the work by Jangamshetti et al. [23] discusses a slightly different problem, in this case the selection of the best sitting for installing a wind farm, choosing between different possible sites of different characteristics. In this work, the key point is the statistics of the wind in each possible site, which are modeled using a Weibull distribution, and the capacity factor of each site, defined as the ratio of average output power to the rated power output. The authors show a study in India in which they choose the best sitting for installing the wind farm out of 54 possible sites.

The aim of this paper is twofold: first, a modified turbines layout optimization problem in wind farms is presented, which includes several novelties in order to make the problem closer to reality than previous approaches. A wind farm shape model, an orography model and the inclusion of benefit/cost terms in the objective function are the main new points included in this paper. In addition, a novel evolutionary algorithm is presented, initially seeded with the solution of a greedy heuristic for the optimal solution of the problem. It will be shown that the proposed approach is able to obtain good and feasible solutions for the problem, with a balance between the computational cost and the quality of the solution obtained.

The rest of the paper is structured as follows: next section summarizes the main previous approaches on wake and cost models used in the literature. Section 3 presents the main novelties included in the optimization model considered in this paper. Section 4 presents the greedy-constructive heuristic proposed, which will be used to seed the evolutionary algorithm presented in Section 5. The experimental part of the paper is shown in Section 6, and Section 7 closes the paper giving some final conclusions.

2. Background: turbines' wake and most used cost models in the literature

In this section the main wake and cost models used in the literature are described. The most used wake model in the literature was first proposed by Mosetti et al. [3], and applied later in many following works such as [4,5,16,21]. Though it is simple (and therefore somehow far away from a realistic wake) it has been profusely used, since it can be complicated with extra constraints to make it closer to reality, and it can be used to compare different algorithms in the same conditions. Fig. 1 shows and schematic of the wake model considered. This model has been simplified by applying the continuity equation in the control volume in Fig. 1:

$$\rho u_0 A_0 \;=\; \rho u_1 A_1 \;=\; \rho u_i A_i \tag{1}$$

So assuming that wind speed will reduce in a units its speed after passing through a turbine:

$$\rho(a u_0) A_r + \rho u (A_1 - A_r) \;=\; \rho u A_r \tag{2}$$

where $A_1 = \pi r_1{}^2$, $A_r = \pi r_r{}^2$ and $r_1 = \alpha x + r_r$. Substituting in Equation (2):

$$u \;=\; u_0\left[1 - \left((2a)/[1+\alpha(x/r_1)]^2\right)\right] \tag{3}$$

where u_0 is the mean wind speed, a is the axial induction factor, x is the distance downstream from the turbine, r_r is the downstream rotor radius and α is the entrainment constant. In addition, r_1 and the turbine coefficient C_T can be calculated from r_r and a, through the so-called *Betz* equations:

$$r_1 \;=\; r_r\sqrt{((1-a)/(1-2a))}, \tag{4}$$

$$C_T \;=\; 4a(1-a) \tag{5}$$

Finally, the entrainment constant α can be empirically calculated as:

$$\alpha \;=\; (0.5)/(In(z/z_0)), \tag{6}$$

where z is the hub height of the wind turbine, and z_0 is the surface roughness.

Using these equations, and assuming that the kinetic energy deficit of a mixed wake is equal to the sum of the energy deficits,

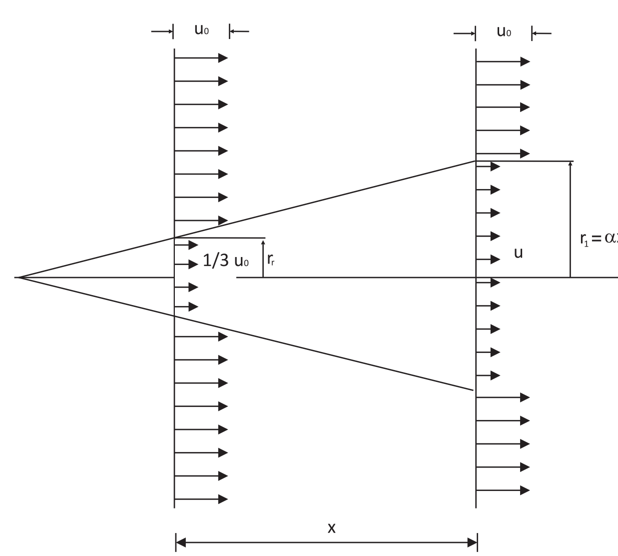

Fig. 1. Schematic of a wake model.

the resulting wind speed downstream of N turbines can be calculated as follows:

$$\left(1-\frac{\overline{u}}{u_0}\right)^2=\sum_{i=1}^{N}\left(1-\frac{u_i}{u_0}\right)^2 \tag{7}$$

The power equation given in [3–5] is the following:

$$P_{total}=\sum_{i=1}^{N}0.3u_i \tag{8}$$

Regarding the cost modeling, in [3,4] is assumed that the non-dimensionalized cost/year of a single turbine is 1, and a reduction in the cost of each turbine when a large number are installed, the total cost/year for the entire wind farm is:

$$cost=N\left(\frac{2}{3}+\frac{1}{3}e^{-0.00174N^2}\right) \tag{9}$$

So the genetic algorithms presented in [3,4] use as objective function the following:

$$g=\frac{cost}{P_{total}}. \tag{10}$$

In [5], using the same wake and cost modeling, a different objective function is considered:

$$g=w_1 cost_m+w_2\frac{1}{P_{total}} \tag{11}$$

$$w_1+w_2=1 \tag{12}$$

where $cost_m$ is the per unit value of cost/year of the whole wind farm. Equation 11 not only optimizes the placement of wind turbines, but also has control on cost.

In [6] a novel cost model based on profitability of investments in the wind farm was presented. Basically, this model is based on the following objective function to be maximized:

$$NPV(x,i,t)=\frac{N_1(x)}{i+1}+\ldots+\frac{N_t(x)}{(i+1)^t}+IC(x), \tag{13}$$

where IC is the initial capital investment, N_k stands for the net cash flow of the kth year, i is the discount rate (capital cost), t is the number of years spanned by the investment and finally x is the solution vector containing the location and height of the wind turbines.

3. Optimization model considered in this work

This section presents the optimization model assumed in this paper. Several points have been included in this model to make the problem closer to a real wind farm design than previous approaches. The main novelties in this model are the inclusion of the wind farm shape, an orography model and a cost model based on benefit/investment terms.

3.1. Wind farm shape model

Previous approaches in the literature have not taken into account the problem of the wind farm shape. Basically the majority of previous approaches consider squares wind farms, divided into cells where turbines could be positioned [3,4]. This square-based approach is interesting since it introduces a nice way of managing the different possible points where a turbine can be installed, but the problem is that it cannot model in a realistic way the design of a real wind farm. In this paper an easy way to consider different shapes for the wind farm is proposed, keeping square cells to model a possible point to locate a wind turbine. The idea is really simple: over a square of length $K \times K$ cells which serves as a background, a binary template $\mathcal{T}$ $(K \times K)$ which describes the *zones allowed* to install turbines is defined. The elements of $\mathcal{T}$ are defined in such a way that $\mathcal{T}_{ij}=1$ stands for a point included in the wind farm area, and $\mathcal{T}_{ij}=0$ stands for a point outside of the wind farm. Note that with this simple idea almost any shape for the wind farm can be considered. As an example, Fig. 2 shows the square background in black, and the allowed zone (described by binary matrix $\mathcal{T}$) in white.

3.2. Wake, orography model and wind speed simulation

In this paper the wake model previously described in Section 2 is considered. Though it is a simple model, it works really well to simulate a real turbine's wake, obtaining a good balance between model's complexity and final performance. Moreover, several new concepts are considered in the problem formulation tackled in this work: first of all, note that none of the previous approaches to the problem takes into account the wind farm's orography or variations on wind speed. The existence of hills within the wind farm makes that the wind speed is different at the top of the hill or at the bottom of the corresponding valley. In order to take this important point into account, the concept of *wind speed multipliers* is included in the problem definition, in such a way that a higher point will be characterized by having a larger wind multiplier. Thus, when the wind speed associated to a given point in the wind farm is modified by means of the wind multiplier, the orography of the wind farm is being taken into account. Fig. 3 shows an example of the wind multipliers in the previous wind farm example. Red areas stand for the largest wind multipliers, whereas blue areas stand for the smallest wind multipliers. This can be obtained by means of different software like CFD etc.

The wind speed modeling in a given point of the wind farm has been calculated in the following way: for each direction of the wind rose in the wind farm considered, a set of Monte Carlo simulations of t years wind are carried out, using a Weibull probability density function for the wind speed module. The result of the Monte Carlo

Fig. 2. Example of the template to generate the wind farm shape.

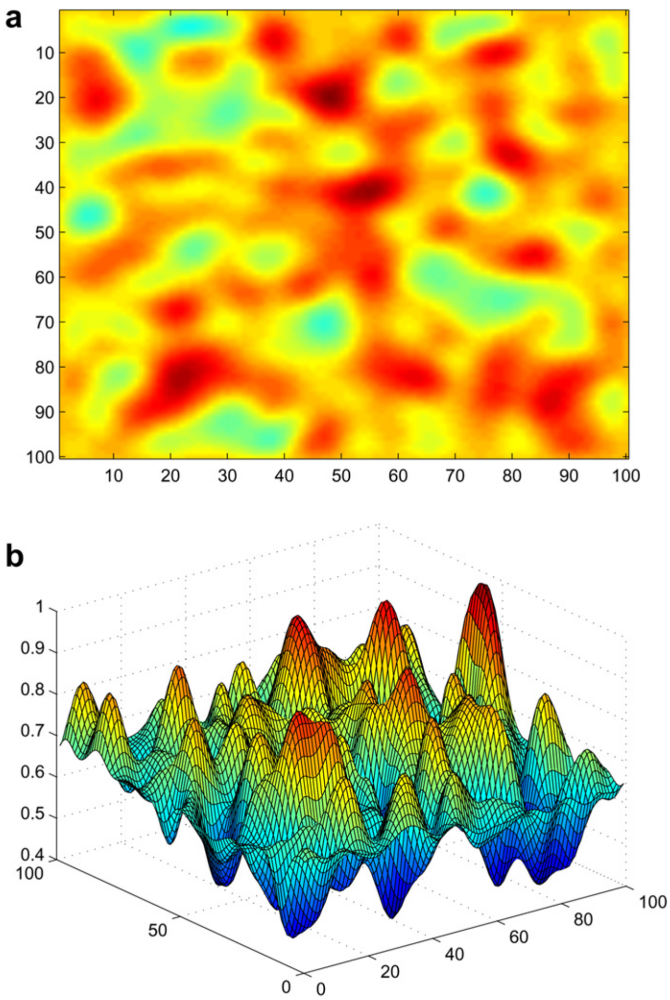

Fig. 3. Example of wind speed multipliers and orography model induced; (a) wind speed multipliers; (b) Orography model induced by the wind multipliers.

simulation is weighted by the corresponding probability extracted from the wind rose and by the wind speed multipliers (in order to include the orography of the wind farm). The power curve shown in Fig. 4 is used to obtain the power production associated to the wind speed in a given wind turbine.

3.3. Cost model

The cost model used in this work is based on a simplified model of investment/benefit considerations, similar to the one proposed in [6]. Specifically, the cost model considered in this paper includes wind turbines installation cost (C_i) and connection between turbines and road construction costs (C_{ij}^C), modeled as the Euclidean distance between turbine i and j. Also, the considered model includes the net benefit obtained from the energy produced in t years (B_t). All these parameters are measured in Euros. The objective function to be maximized is:

$$\varphi(\boldsymbol{\Xi}) = B_t - N \cdot C_i - \sum_{i=1}^{N} \sum_{j<i} C_{ij}^C \tag{14}$$

where N stands for the number of wind turbines installed in the wind farm. Note that no alternative costs such as the operational costs (OPEX) are considered in this objective function. However, it is good enough to show the performance of the different compared algorithms.

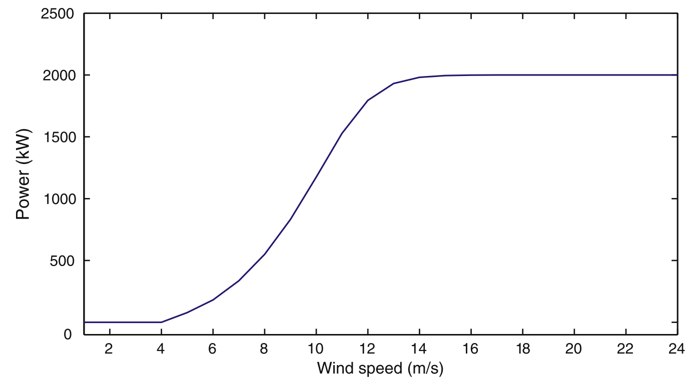

Fig. 4. Power curve used in the simulations of this paper.

4. GHWTP: a greedy-constructive heuristic for wind turbines positioning

In this paper an heuristic approach to solve the wind turbine location problem with the model considered in this paper (see previous section) is first proposed: the Greedy Heuristic for Wind Turbines Positioning (GHWTP). There are previous works in the literature dealing with heuristics for optimal positioning of wind turbines in wind park [24]; in this paper an ad-hoc heuristic approach is presented, which takes into account all the peculiarities of the considered optimization model.

The proposed heuristic can be considered a greedy-constructive approach, based on exploiting the best locating points in terms of the objective function ϕ. The heuristic starts with the location of the point in the wind farm with the maximum wind speed (simulated in the way described in Section 3.2). A wind turbine is located at this point. The wind speed values in other points of the wind farm are then modified applying the wake model, taking into account the wind rose, and then another point to locate the second wind turbine is selected by considering the point which maximizes the objective function ϕ, i.e. point with maximum wind speed and with the minimum possible value of the connection term among turbines. This procedure is carried out until the desired number of wind turbines (N) are positioned in the wind farm.

(1) Locate the point in the wind farm with maximum wind and positioning there the first wind turbine.
(2) Correct the wind speed in neighbor points to turbines taking into account the wake model and wind rose considered.
(3) Locate the point in the wind farm which maximizes Equation (14), and set there the following wind turbine.
(4) If N wind turbines have been installed, then stop. Otherwise go to step 2.

Note that the GHWTP takes into account the best points in terms of wind speed, but also in terms of the distance among wind turbines in Equation (14). The main characteristics of this heuristic is that it is really fast, and provides a reasonable solution in terms of the objective function given by Equation (14). However, it is not an optimal approach, since the positioning of the first wind turbines affect to the positioning of the last ones, and suboptimal solutions may appear.

5. The evolutionary algorithm proposed

Evolutionary algorithms (EAs) [25–27], are robust problems' solving techniques based on natural evolution processes. They are population-based techniques which codify a set of possible solutions to the problem, and evolve it through the application of the so-called *evolutionary operators* (26). Next the main characteristics of the evolutionary algorithm proposed in this paper are described, including the algorithm's initialization and selection, crossover and mutation operators proposed.

(1) Generate an initial population of μ individuals (solutions). Let t be a counter for the number of generations, set it to $t = 1$. Each individual is taken as a matrix of integer vectors $\Xi = (x_i, y_i)$, $i = 1, \ldots, N$, where each x_i stands for the x-coordinate of turbine i in the background square considered, and each y_i stands for the y-coordinates ($x_i = 1, \ldots, K$, $y_i = 1, \ldots, K$). Note that every location point of a given solution Ξ, lets say (x, y), must fulfill a number of requisites to be considered as feasible: first, all the location points should be within the wind farm surface, i.e, the associate value in matrix $\mathcal{T}$ must be 1 ($\mathcal{T}_{xy} = 1, \forall\, x, y$). Second, a given turbine situated at a point (x, y) must be at least at a distance $\mathcal{D}$ of any other turbine. The initial individuals of the population are generated in such a way that these constraints are fulfilled.
(2) Evaluate the fitness value for each individual Ξ of the population using the problem's objective function ϕ.
(3) Generate an offspring population, of length μ, applying one-point crossover operator [26] and mutation operator. The crossover operator is applied in the traditional way, Fig. 5 shows an example. On the other hand, mutation operator is carried out by randomly changing couples of specific points (x_i, y_i) to (x'_i, y'_i), see Fig. 6 as an example.
(4) Correct the offspring population in such a way that all their individuals are feasible (fulfill the problem's constraints). Note that the crossover operator may produce solutions within a distance $\mathcal{D}$ of another turbine, and mutation operator, in addition, may produce solutions which are outside the wind farm points defined by matrix $\mathcal{T}$. In order to correct these unfeasible solutions, a modification of unfeasible points is applied after each round of crossover and mutation, by using two random numbers $r, s \in [-2\mathcal{D}, 2\mathcal{D}]$: a given unfeasible point (x, y) is modified to $(x + r, y + s)$ until it is feasible.
(5) Selection: Pass the best individual found so far in the evolution to the next generation. Conduct then pairwise comparison over the union of parents and offspring remaining: for each individual, p opponents are chosen uniformly at random from all the parents and offspring. The best individual in these p is selected to survive for the next generation. This process is repeated until a new parent generation of μ individuals is obtained.
(6) Evaluate the fitness value for each individual Ξ of the new parent population using the problem's objective function φ.
(7) Stop if the stopping criterion is satisfied, and if not, set $t = t + 1$ and go to Step 3. In this case, the stopping criterion established is that the best solution found by the algorithm is not improved during $\mathcal{K}$ generations, or, alternatively, the algorithm reaches to a maximum number of generations *max_ite*.

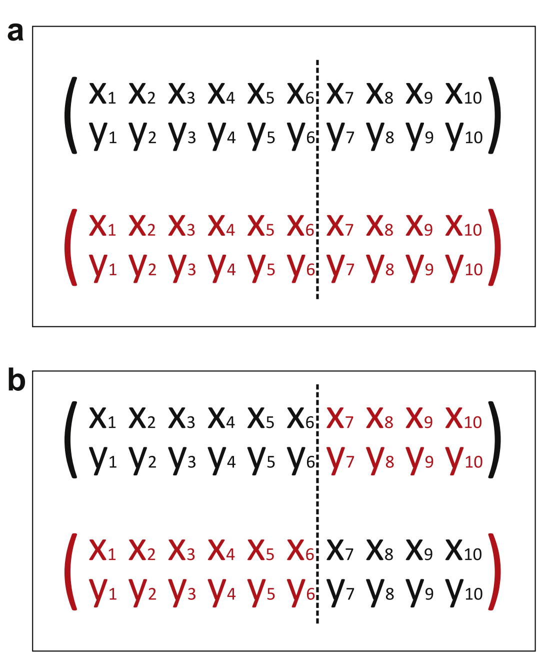

Fig. 5. Example of the one-point crossover implemented in the proposed EA, in an example with $N = 10$ wind turbines; (a) initial couples of individuals and random-picked crossover point; (b) Final crossed individuals.

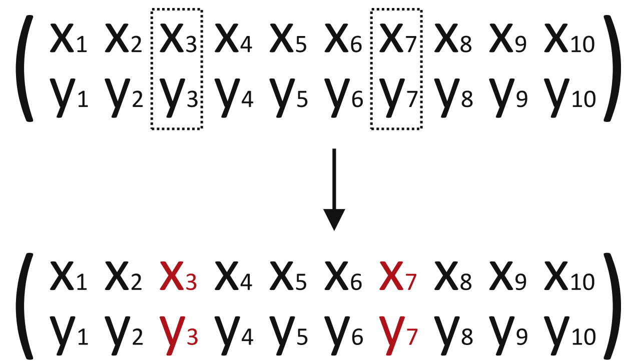

Fig. 6. Example of the mutation operator implemented: first a number of points are randomly selected to be mutated. Second, new values are randomly selected in $K \times K$ and substitute previous values.

5.1. Seeding the EA with the GHWTP

This paper also deals with the idea of using the solution obtained by the GHWTP as starting point for the EA (seed the EA). Many researchers have proposed to seed EAs with good initial solutions whenever it is possible, obtaining important improvements in the algorithm's convergence and quality of the solutions obtained. In this case it is proposed to seed part of the initial EA population with the GHWTP solution and some variations of this solution (obtained by means of mutation), and also to include randomly generated individuals to complete the initial population of the EA.

This way of initializing the evolutionary algorithm should improve the final solution obtained by the EA, since due to the elitist selection implemented, the best individual in a generation is maintained in the next generation. Thus, at least the EA seeded by the GHWTP will obtain this solution as the best one. Moreover, it has been found that the seeded EA improves significantly the GHWTP solution, and the convergence of the algorithm is much better than the EA without this intelligent initialization, as will be shown in the experimental results obtained in this paper.

6. Experiments and results

In order to show the performance of the proposed seeded EA, a large amount of experiments have been analyzed, in different randomly obtained scenarios. First, a randomly generated wind farm shape is considered (given by a $\mathcal{T}$ matrix), shown in Fig. 2. Over this wind farm shape, 15 different sets of wind speed

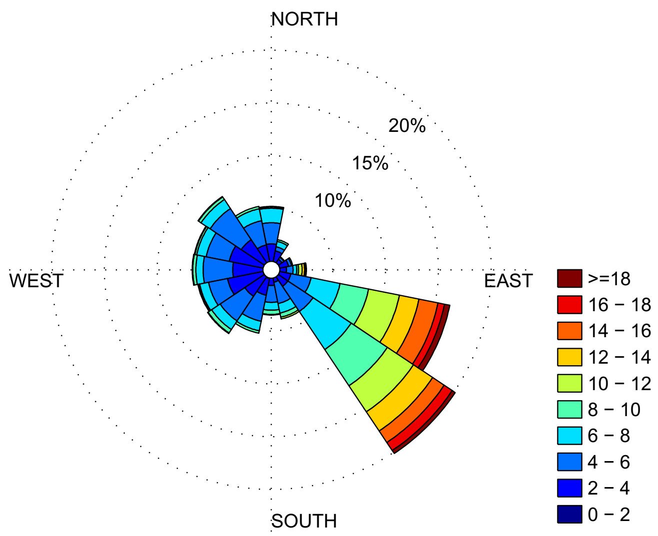

Fig. 7. Wind rose considered in the simulations of this paper.

multipliers have been obtained to model different orography for the wind farm. In these 15 different scenarios (instances) the GHWTP, EA and Seeded EA (SEA) have been run, and their performances compared. Fig. 7 shows the wind rose considered, extracted from a real wind farm in southern Spain. Weibull's distribution parameters used in the model of the wind speed are $\lambda = 10$ and $\beta = 1.6$. The positioning of $N = 20$ similar wind turbines is considered, each characterized by the power curve displayed in Fig. 4. The cost of each tower has been estimated to be $C_i = 10^6$ Euros. Other parameters of the simulations are the following: a basic cell size of 10 m $\times$ 10 m is considered, with $K = 500$ and $\mathcal{D} = 90$ m. The cost for the connection of wind towers and road construction (C^c_{ij}) has been set to 10^5 Euros/Km. Regarding the calculation of the estimated benefit $B_t(\Xi)$ in the wind farm: 75 Euros/Mwatt-h, 3000 effective-hours/year and a period of $t = 10$ years of simulation are the parameters values considered in the simulations. Regarding the EAs, values of $\mu = 50$, $p = 10$, $\mathcal{K} = 75$ and $max\_ite = 500$ have been set in the algorithm.

Table 1 shows the comparison between the GHWTP, EA and SEA algorithms in the two wind farm shapes considered, respectively. Note that the EA is able to obtain better solutions than the GHWTP in all the simulations. The SEA, however, outperforms the GHWTP and the EA in all the experiments carried out. Note the differences in performance obtained between the SEA and EA. It indicates that

Table 1
Objective function values (in Euros/10^7), in the 15 different simulations performed, obtained by the GHWTP heuristic, Evolutionary Algorithm and Seeded Evolutionary Algorithm proposed.

# Instance	GHWTP	EA	SEA
1	2.063	2.748	4.992
2	1.844	4.569	5.852
3	2.454	4.671	5.936
4	1.752	4.035	4.728
5	3.264	4.565	4.873
6	1.945	3.768	5.576
7	1.899	2.913	3.813
8	1.841	4.520	4.992
9	1.854	4.368	4.731
10	1.670	3.953	4.467
11	1.755	3.242	4.881
12	0.883	2.399	3.374
13	2.247	3.660	4.853
14	1.684	3.206	4.040
15	2.851	3.648	4.685

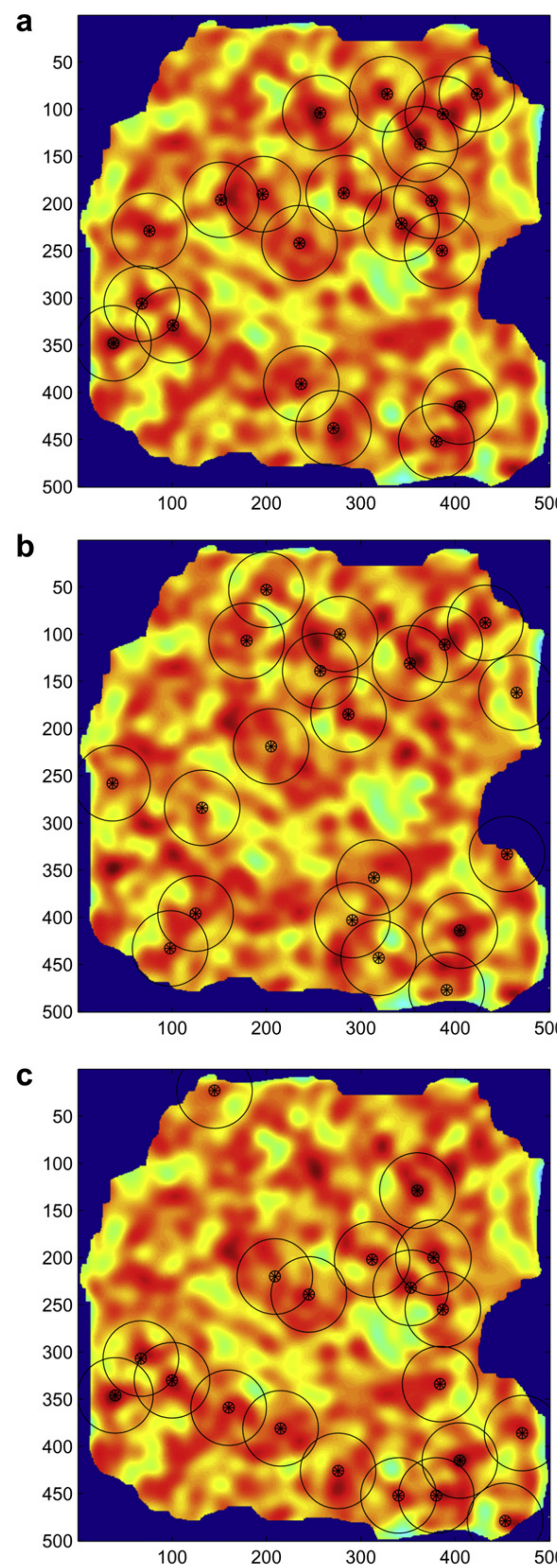

Fig. 8. Final wind turbines disposition, security radius and wind multipliers; (a) GHWTP; (b) EA; (c) SEA.

a good initialization procedure leads to a much better performance of the algorithm. On the other hand, in these tables it is possible to see the differences introduced by considering the orography of the wind farm, since the only differences between the different instances in both cases is the orography considered (random values of wind speed multipliers).

Fig. 8(a), (b) and (c) show an example of the solution obtained by the GHWTP, EA and SEA, respectively, in one instance of the problem. It is possible to see that the solutions obtained by the three algorithms considered fulfill the constraint given by the minimum deployment distance $\mathcal{D}$ (marked in the figures by the corresponding radius around a positioned wind turbine).

7. Conclusions

In this paper a novel evolutionary algorithm has been considered, initially seeded with the solution of a greedy approach, in a problem of optimal location of wind turbines in wind farms. A novel optimization model has also been proposed, which includes some new aspects such as wind farm shape, orography and different costs in the objective function. Several experiments have been carried out, where the good performance of the seeded evolutionary in the design of wind farms has been shown.

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