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Retraction: Solving the problem of optimizing wind farm design using genetic algorithms (*IOP Conf. Series: Materials Science and Engineering* **872** 012029)

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Solving the problem of optimizing wind farm design using genetic algorithms

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Abstract. Renewable energies have become a topic of great interest in recent years because the natural sources used for the generation of these energies are inexhaustible and non-polluting. In fact, environmental sustainability requires a considerable reduction in the use of fossil fuels, which are highly polluting and unsustainable [1]. In addition, serious environmental pollution is threatening human health, and many public concerns have been raised [2]. As a result, many countries have proposed ambitious plans for the production of green energy, including wind power, and consequently, the market for wind energy is expanding rapidly worldwide [3]. In this research, an evolutionary metaheuristic is implemented, specifically genetic algorithms.

Keyword(s): Wind Turbines, Wind Fields, Wake Effect, Combinatorial Optimization, Genetic Algorithms.

1. Introduction

The transformation of wind energy into electrical energy is carried out through wind turbines, which are generally grouped or distributed in wind farms with the purpose of exploiting the yields associated with economies of scale, such as: lower installation and maintenance costs [4]. Design optimization is one of the methods to increase the expected energy production in a wind farm [5]. Besides, the fact that good wind farm design increases energy production simultaneously guarantees the project's profitability. Inadequate design or distribution of wind turbines could lead to lower than expected energy production, resulting in low profits. The problem of optimizing wind farm design is to find an optimal allocation of wind turbines at a given site so that the energy output is maximized. This strategic problem is extremely difficult to solve in practice due to the size of the instances in real applications as well as the presence of non-linear aspects to be considered [6]. A very important non-linear aspect to take into account for the optimal design of a wind farm is a phenomenon of interaction between two or more wind turbines. The wake effect is a phenomenon derived from the interaction where, if two turbines are located near each other, the first turbine that interacts with the incident wind creates a shadow or turbulence over a second turbine behind the first one.
The scientific community has catalogued the wind farm design optimization problem as an NP-Hard optimization problem, which means that there is no algorithm that can solve it in a polynomial computational time. Despite the enormous growth of projects related to the construction of wind farms, there is little information about the optimization of the wind turbine positioning problem [7]. Because of this, the idea of implementing a metaheuristic approach

arises to provide a good quality solution in a reasonable computational time to this optimization problem. In the literature, a considerable amount of heuristic techniques and methods have been implemented to solve the wind field optimization problem, among which the genetic algorithms [7] [8] stand out, although other algorithms such as the ant colony algorithm [9] and the particle swarm algorithm [10] are also presented.
Therefore, this paper proposes the implementation of an evolutionary metaheuristic to optimize the locations of wind turbines in order to achieve the best configuration or design of the wind field, ensuring the highest amount of installed energy considering the energy losses caused by the wake effects through the Jensen model.

2. Methods

This section explains each of the methods used in this research to solve the problem of wind field design. It is worth mentioning that for the purposes of this paper, the feasibility analysis of the land or windy site where a field is to be built is omitted because the interest is focused on optimizing installed wind fields, in installation plans or those for which at least an initial design or configuration is counted [11].
The first method corresponds to the discretization of the wind field. In order to reduce the complexity of the optimization problem, the discretization or division of the wind farm through small cells or grids is proposed. In the present research, only the optimization of flat wind fields, whether square or rectangular, and wind turbines of the same height is considered. Figure 1 shows a proposed design or small instance for a 1 x 1 km wind farm. In this figure, the discretization of the terrain can be seen [12]. The center of each grid corresponds to a possible location called centroid (represented by a ring), in which a wind turbine could be assigned or installed.
For this particular scenario there is a predefined set of 16 possible discrete locations with dimensions of 250 x 250 m each. In this proposed scenario, there is a total of 8 wind turbines installed (represented by the black filled rings), as well as considering an incident wind with initial speed U_0 and with a dominant direction from East to West. For this small instance, the number of possible combinations or ways to design the wind farm amounts to a total of 12,870 [13]. Discretization is a very useful method because if a wind farm will not be discretized, the algorithm would invest a lot of time in finding a solution within a continuous solution space.

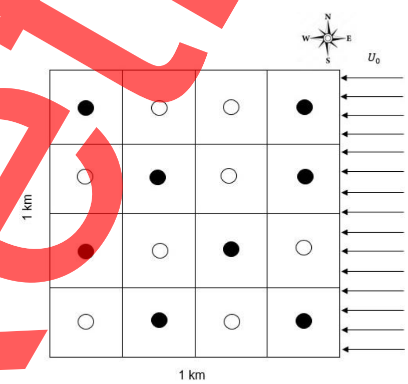

Figure 1. Discrete wind field.

The second method corresponds to the modeling of the wake effect. The modeling of the wake effect for calculating the wind speed deficits has been the cause of many studies, so several models have been proposed to analyze the characteristics of this aerodynamic phenomenon, such as: speed with which the wake effect expands, diameter of the effect, etc. Therefore, for the modeling of the wake effect, this research considers the Jensen model proposed in [14], which is an equivalent model to the one proposed in [15].
The third method corresponds to genetic algorithms [16]. The equations in (1) present the objective function to be optimized. This function represents the total energy produced by the

wind field by means of the individual sum of the energy generated by each wind turbine. Table 1 shows the pseudocode of the genetic algorithm.

$$Max\ Z = \sum_{i=1}^{N} P_i\, x_i$$

$$s.a. \qquad x_i \leq 1$$

$$x_i \in \{0,1\} \tag{1}$$

Where: Z = Total energy produced.
Pi = Instantaneous energy generated by the i-turbine.
N = Number of wind turbines to be installed.
xi = 1 If a wind turbine is installed at site i.
xi = 0 Other case.

3. Results

This section optimizes a hypothetical wind farm case. The case corresponds to an instance with 100 possible locations and 30 wind turbines to be installed. Figure 2 shows the characteristics and dimensions of the wind farm. In this case, the wind farm measures a total of 16 km2 (4 x 4 km). Each discrete grid of the wind farm has a dimension (resolution) of 400 x 400 m. The rotors of the wind turbines considered in the optimization measure a radius of 40 m. The height of the wind turbines is 60 m. The surface roughness was considered to be 0.14 m, which is typical for wind farms built on land with some low obstacles [16].

Table 1. Pseudocode of the genetic algorithm.

Genetic Algorithm
t ⟵ 0; /* iteration counter */
initialize(Pa) / *Initialize the population */
while *there is no stop criterion (t, Pa)* **do**
Parent ⟵ *selection(Pa); /*Parent selection*/*
Children ⟵ *reproduction (Parents) /*Cross*/*
*mutation(Children) /*mutating* children*/
*evaluate (Children) /*evaluate* children*/
*newGeneration = replacement(Pa, children)/*replacement* the population by the current one*/
t ⟵ *t+1 /*One more* iteration*/
end while
Retracing: best solution found.

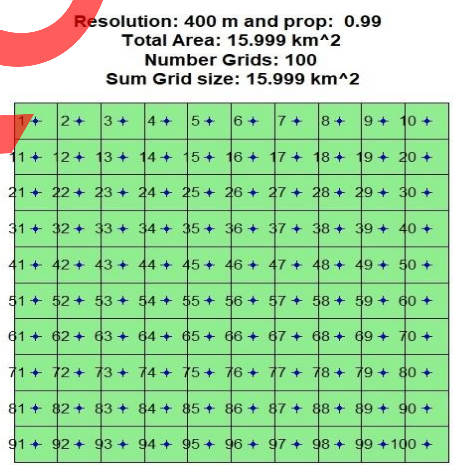

Figure 2. Characteristics and dimensions of the wind farm to be optimized.

The values of the parameters or input variables used in the algorithm to execute the optimization run are presented in Table 2.

Table 2. Input variables for optimization algorithm.

Variable from entry	Value	Description
Iteration	100	Number of iterations or generations
Selection	"FIX"	This value of the selection variable chooses a constant value of 50% of the total population to procreate new solutions (individuals) in the next generation
Crossing	"RAN"	This value of the crossover variable divides the genetic code into random locations
Mutation	0.006%	Mutation rate that randomly modifies part of the genetic code of individuals to avoid premature convergence in local optimums
Elitism	"True"	This value of the elitism variable activates elitist selection, which ensures that the best individuals are selected in each iteration

Figure 3 shows the wind rose, which indicates the direction and speed of the wind considered in this scenario. Therefore, in this scenario, an incident wind with a direction of 45° (Northeast - Southwest) with a uniform speed of 12 m/s is considered.
The use of the values of the parameters of crossing, mutation and selection is based on the fact that a previous investigation revealed that under these values the algorithm is able to explore and converge towards very high-quality solutions investing little computational effort.
Therefore, considering the data and specifications described above, the best design or configuration solution for the hypothetical wind farm is presented in Figure 4.

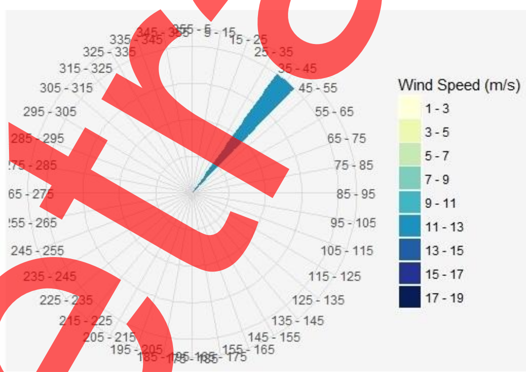

Figure 3. Incident wind direction and speed.

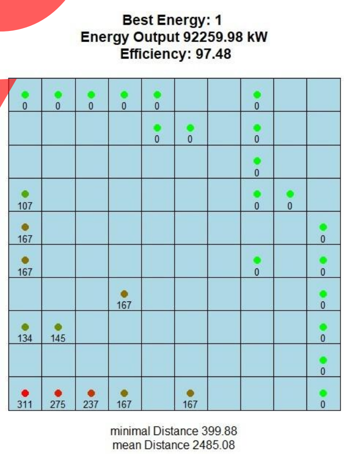

Figure 4. Best design solution found by the algorithm

The total energy expected with this configuration solution is 92259.98 kW with an efficiency of 97.48%. Likewise, Figure 5 presents the points (way of representing the wind turbines to scale) within the grids where the wind turbines are installed according to the best solution found. The colors and values shown below these points indicate energy loss caused by the wake effects. The points where the energy losses caused by the wake effects are minimal are represented in green, while the points where the energy losses in red. Similarly, the below figure also shows the minimum distance and the average distance at which the wind turbines are located according to the best solution found. The CPU time that the algorithm invested to find such solution using 2-core parallel computing was 395.02 seconds.

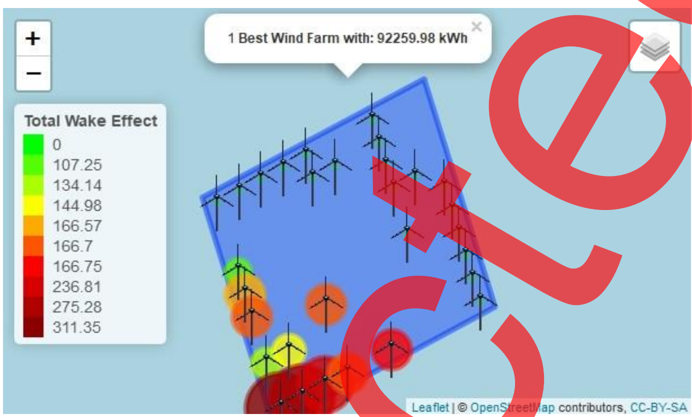

Figure 5. Alternative representation of the wind farm design

Above figure shows the identical solution presented in Figure 4, but from a more real or wind farm-like perspective. In this figure it is also possible to see that the wind turbines shaded in green are the least affected by the wake effects, while those shaded in red are affected to a greater extent by the wake effects.
Figure 6 shows the percentage progress of the amount of energy produced (energy efficiency) in each of the generations or iterations, the maximum percentage values reached by an individual or solution in each generation are represented in green, the average percentage values in blue and the minimum values in red. Figure 8 presents the development of the amount of energy produced (in kW units) in each iteration, it is interpreted in the same way as Figure 7, only in energy units.

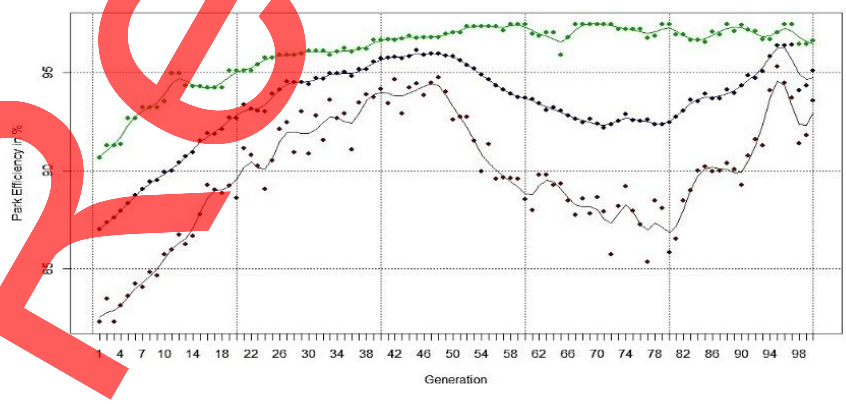

Figure 6. Progress of the fitness values in percentage.

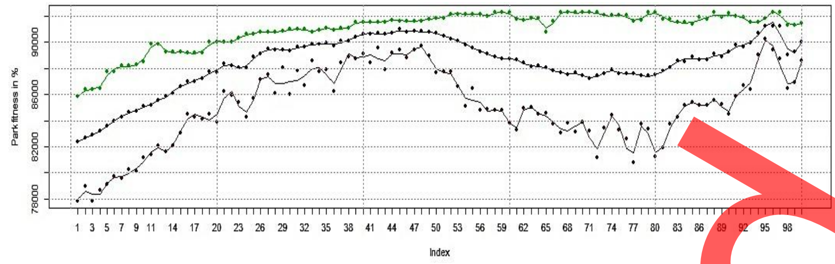

Figure 7. Progression of proficiency values in units of energy.

Figure 8 shows the number of individuals from each population throughout the iterations. The number of individuals in each iteration is counted after the fitness, selection and crossing function. The number of individuals in each iteration is the same for both the fitness function and the crossing function. The black points represent the number of individuals after the fitness function, the red points the number of individuals after the selection function and the green points indicate the number of individuals after crossing.

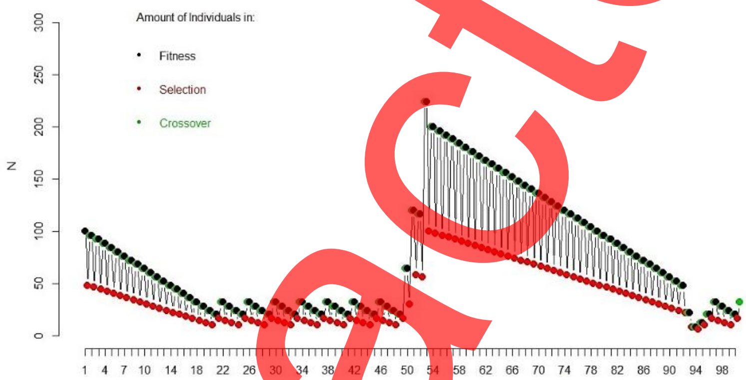

Figure 8. Number of individuals in each iteration.

Figure 9 shows the influence of the mutation according to the energy efficiency values. Similarly, the figure shows the evolution of energy efficiencies over all generations.

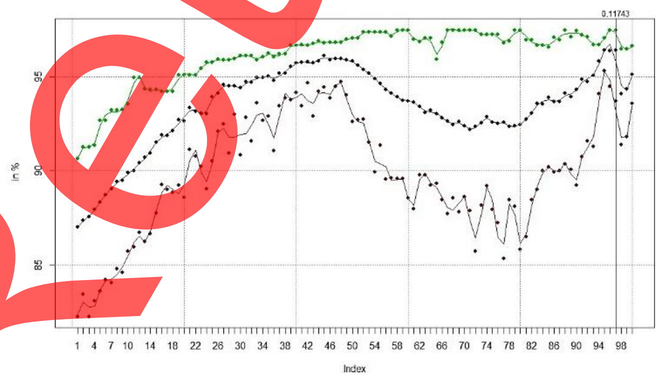

Figure 9. Influence of variable mutation on the search for new solutions.

The maximum energy efficiency values found in each iteration are represented in green, the average values in blue and the minimum values in red. The vertical lines indicate in which iterations a variable mutation rate was used instead of a fixed mutation rate. In this case, the algorithm just needed to activate the variable mutation once in order to explore other regions of the solution space. The algorithm is designed to activate a variable mutation rate. Figure 10 shows the evolution of the wind farm energy efficiencies during each generation, as well as presents vertical green lines for the generations in which the selection percentage was higher than 75%.

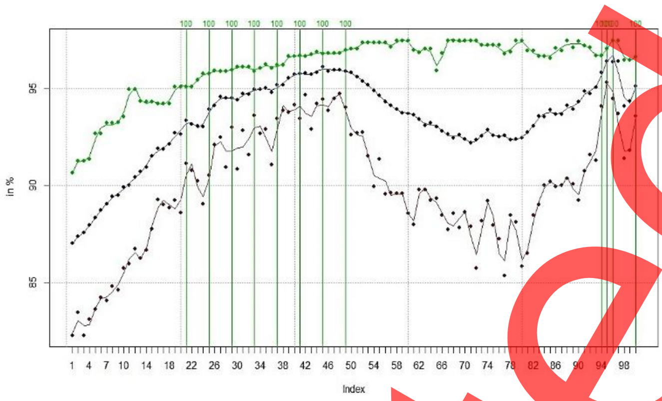

Figure 10. Influence of the selection of individuals in each generation.

Figure 11 presents the energy efficiencies for each generation, as well as the vertical red lines for the generations where the number of cross parts was greater than 2. Therefore, according to this figure the algorithm used 3 cross parts with the same purpose of avoiding the extinction of the population. The occasions in which the algorithm used 3 crossbreeds were sufficient because, according to Figure 9, once the number of crossbreeds was increased, the population size increased significantly as it happened in the iteration t = 52.

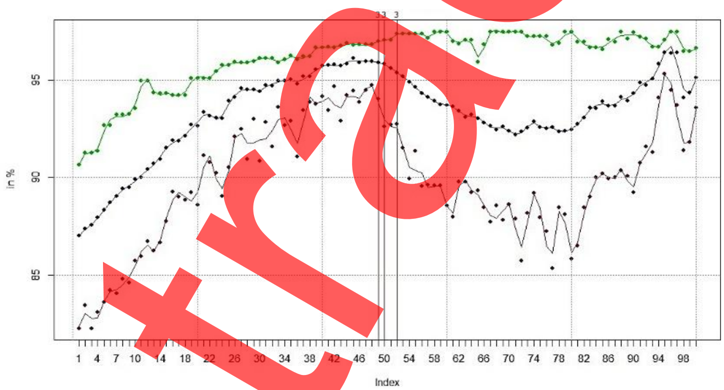

Figure 11. Influence of the crossing of individuals with 3 crossing parts.

4. Discussion

This research briefly addressed the boom that wind energy has taken on worldwide, as well as the difficulties that wind farm designers could face, such as the problem of optimizing wind farm design. According to this problem, this paper focused on showing and attacking the phenomenon that mainly affects the optimal use of the wind resource in order to obtain the highest production of green energy. Despite the fact that a proposed scenario was solved in this research, the optimization algorithm described in this manuscript can be implemented in practice because the wake effect model considered (Jensen's model) corresponds to an exceptional approach to reality to solve practical instances. Therefore, the algorithm can be used by wind farm designers because they often resort to an inefficient design since they do not consider the energy losses caused by the wake effects, resulting in the inability to achieve the main objective of a wind farm, which is to generate the maximum amount of energy by exploiting the wind resource from a defined number of wind turbines.

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