The optimal configuration of turbines location in a wind farm using a Genetic Algorithm

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Abstract— *The placement of wind turbines is a key technology for wind farm configuration, but the automatic placement of turbines is always still a difficult problem. The objective of every wind farm designer is producing as maximum as possible of energy, with minimal cost of installation The improved wind and turbine models are formulated into an optimal control framework in terms of minimizing the cost per unit energy of the wind farm. In this study, a code Wind Farm Optimization using a Genetic Algorithm (WFOAG) is developed for optimizing the placement of wind turbines in wind farm to minimize the cost per unit power produced from the wind farm. A genetic algorithm is employed for the optimization. WFOAG is validated using the results from previous studies.*

Keywords— wind farm; cost model, wake effect, optimization, wind turbine, genetic algorithm.

I. INTRODUCTION

Today, the part of production from renewable energy sources has increased dramatically compared to fossil fuels. This is generally due to some factors such as the high and rising price of traditional fossil fuels, during this, great social and environmental concerns and institutional support undertake to reduce foreign fossil fuels.

Many countries have already invested in green energy and they will invest even more because of dwindling resources of fossil fuels, the commitment of the Kyoto Protocol and the obligations for all countries with regard to the protection of the environment. By focusing on the types of renewable energy, it is a well known fact that wind energy has increased the most. That is why the development of an efficient tool for the design and construction of wind farms has a special importance. The design of the wind farm involves several factors. These range from maximum desired installed capacity for the wind farm, site constraints, noise assessment for noise sensitive dwellings, visual impact and the total cost. The fundamental aim, while designing a wind farm, is to maximize the power production while reducing the total costs associated with the wind farm. 'Micro-siting' is the process of optimizing the layout of the wind farm. This process is facilitated by the use of wind farm design tools (WFDTs) which are commercially available.

In this work, wind turbine placement in a wind farm is optimized using an objective function that represents the cost per unit power produced by the wind farm for a particular wind distribution function. The wind distribution function, in general, represents a model of wind variations in speed and direction averaged over a year, or many years. A genetic algorithm is employed for optimizing the placement of the wind turbines. An analytical wake model is utilized for modeling wind turbine wakes in the wind farm.

II. LITERATURE REVIEW

Several researchers have utilized analytical wake models to optimize the placement of wind turbines in a wind farm. Use of computational wake models has been rare owing to high computational costs involved in obtaining specific results for each wind condition under consideration. In order to achieve better results, some studies on wind turbines positioning were performed, where different optimization methods and wind farm models were used. The first work that implemented an optimization method for this problem was introduced by Mosetti et al. in 1994 [1], which adopted the genetic algorithm as an optimization tool. The study of Mosetti et al. was to develop an algorithm able to place wind turbines in a defined area where the goals of the optimization were maximizing the production and reducing the cost of implementation. Mosetti et al. opted for simple wind farm and cost modeling, because their focus was the effectiveness of the optimization process. In 2005, Grady et al. [2] attempted the same problem as Mosetti et al. They examined the same three cases as Mosetti. Authors have used the exact same approach as was by Mosetti et al. such as Jensen's analytical wake model and a genetic algorithm for optimization. Grady et al. showed that Mosetti et al.'s results are not optimum. They suggested that the probable cause is that the solution was not allowed to evolve for sufficient generations (i.e., it was not converged to the optimum point). Another work was developed by Marmidis et al. in 2008 [3], which used a different optimization method, the Monte Carlo method. Emami et al.[4] in 2010 proposes an improvement in wind farm layout optimization with the Jansens's wake model by modification of the objective function, which takes into account the efficiency of wind turbines and the wind farm deployment cost.

TABLE 1
DETAILED DESCRIPTIONS OF PAST APPROACHES

Detailed Descriptions / Past Approaches	Objective function	Cost/year	Technique used	Power	Efficiency
Mosetti et al.	Single objective	Same	Genetic algorithm	reported	Not considered a parameter
Grady et al.	Single objective	same	Genetic algorithm	reported	Not considered a parameter
Marmidis et al.	Single objective	same	Monte Carlo simulation	reported	Not considered a parameter
Emami et al.	Multi-objective	same	Genetic algorithm	reported	Considered and calculated in some cases

The literature review gives a clear vision that mostly research in the field of wind farm layout optimization focused only on the wind turbine positioning within the specific area of wind farm [5]. However the research on the wind farm area dimensions and fully utilization of upstream wind velocity is currently lacking in literature. The present work is based on the works mentioned above, as it also uses genetic algorithm as an optimization tool and a simple modeling of a wind farm. Nevertheless, new codifications have been adopted.

III. FORMULATION OF OPTIMIZATION PROBLEM

3.1 Probability density function

The wind speed histogram is approximated by a continuous function called the probability density function. This function expresses the probability (frequency or percentage of time) of occurrence of wind speed.

The probability density function is given by:

$$f(V) = \frac{K}{C}\left(\frac{V}{C}\right)^{K-1} \exp\left|-\left(\frac{V}{C}\right)^{K}\right| \tag{1}$$

The cumulative distribution function is given by:

$$F = \exp\left|\left(\frac{V}{C}\right)^{K}\right| \tag{2}$$

The V value average and standard deviation σ of the distribution are expressed using the Γ function:

$$V = C\,\Gamma\left(\frac{1}{K}+1\right) \tag{3}$$

$$\sigma = C\left|\Gamma\left(1+\frac{2}{K}\right) - \Gamma^2\left(1+\frac{1}{K}\right)\right| \tag{4}$$

Γ is an Eulerian function of the second kind defined by:

$$\Gamma(x) = \int_0^\infty t^{x-1} \exp(-t)dt \tag{5}$$

With $x \geq 0; t = \left(\frac{V}{C}\right)^K$; $(x-1) = \left(\frac{1}{K}\right)$

The integration of $f(v)$ between V and ∞ give the expression of the distribution function $f(v)$. To represent the distribution of the wind frequency using the Weibull distribution, there is a probability density function:

$$f(v) = \left(\frac{k}{C}\right)\left(\frac{V}{C}\right)^{k-1} \exp\left(\frac{-V}{C}\right)^{k} \tag{6}$$

Where f (v) is the probability density at the speed V (m/s), K is the shape of the curve factor (dimensionless), C is the scale of the curve factor in m/s.

3.2 Wake model

Turbines interact with the wind captures part of the kinetic energy and are converted to usable energy. According to the first law of thermodynamics, this energy extraction creates a gap between the outgoing wind turbine and the oncoming wind turbine. Thus, the wind speeds at the rear of the turbine is lower than the wind speed upstream and consequently a reduction in output power is generated by the turbines. The wake effect also causes high levels for turbulence in the wind turbines, giving rise to an additional mechanical strain, which may reduce their lifetime.

Many studies on the wake effect were conducted, and several models have been developed by researchers, as mosaic tile model [6], the Frandsen model [7], Ainslie [6] model, the model Jensen [9] and CFD (Computational Fluid Dynamics) model [10]. The choice of model depends on the desired accuracy of the prediction and the calculation time. A wake models most widely used, developed by Jensen [9], was chosen for this study because it provides sufficient accuracy and a reduction in computation time. The turbine interact with the wind, capture a portion of its kinetic energy and converts it into useable energy, this extraction of energy creates a gap between the outgoing wind turbine and the oncoming wind turbine. Thus, the wind speeds at the rear of the turbine is lower than the downstream speed of the wind, as a result it decreases the production of output energy [11]. The wake effect also causes high levels of turbulence in the outgoing wind turbines, giving rise to an additional mechanical stress, which may affect them, this behavior caused by the turbulent is neglected in this study because it does not affect directly output power. In both works of Mosetti and Grady's [1-2] the model used is similar to the model developed by Jensen [9] in 1986. Here we assume that the movement is kept inside the wake.

For a single turbine, the downstream wake zone will be considered as a trapezoid such that the average speed of the wind can be expressed by the following equation:

$$u = u_0\left[1-\frac{2a}{\left(1+\alpha\left(\frac{x}{r}\right)^2\right)^2}\right] \tag{7}$$

Where α is the entrainment Constant, a is the axial induction factor, x is the distance from the turbine, and r is the radius of the turbine downstream, as shown in Figure 1.

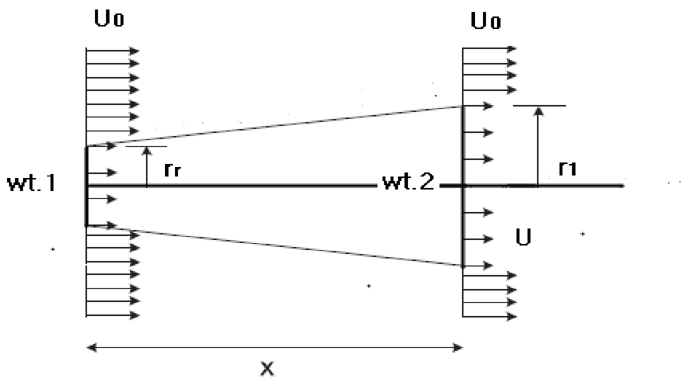


FIGURE 1. Single Wake

The relationships between r, r_r the radius of turbine and C_T the thrust coefficient are represented in the equations:

$$r = r_r\sqrt{\frac{1-a}{1-2a}} \tag{8}$$

$$C_T = 4a(1-a) \tag{9}$$

The entrainment Constant is empirically given by:

$$\alpha = \frac{0.5}{\ln\left(\frac{Z}{Z_0}\right)} \tag{10}$$

Where z is the hub height of the wind turbine, and z_0 is the surface roughness of the site. When the turbine downstream is not completely immersed in a wake, if A_w is the part of the rotor area that is inside the upstream turbine wake, as shown in Figure. 2, the effect of the corresponding deficit must be reduced according to:

$$(U_p - U_0)^2 = \frac{4A_w}{\pi D_0^2}(U - U_0)^2 \tag{11}$$

Assuming that R and r are respectively the radii of the bigger and lower circumferences (general but not necessarily the wake and rotor ones respectively) and X is the distance between their centres, the overlapped area A_w yields:

$$A_w = R^2\cos^{-1}\left(\frac{R^2+X^2-r^2}{2RX}\right) - R^2 0.5\sin\left(2\cos^{-1}\left(\frac{R^2+X^2-r^2}{2RX}\right)\right) + r^2\cos^{-1}\left(\frac{R^2-X^2-r^2}{2RX}\right) - r^2 0.5\sin\left(2\cos^{-1}\left(\frac{R^2-X^2-r^2}{2RX}\right)\right) \tag{12}$$

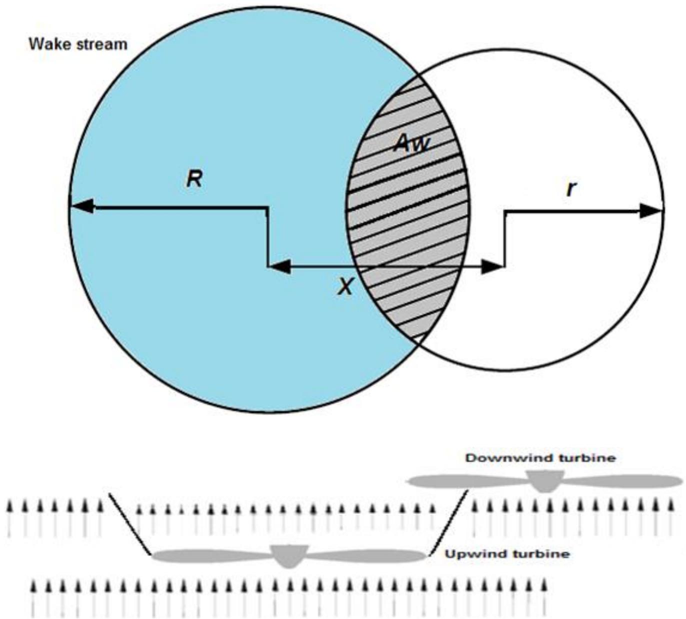


FIGURE 2. The Shade Area of A Downstream Wind Turbine in Partial Wakes.

For multiple wakes we supposed that the loss of kinetic energy is equal to the sum of the energy losses. So, for N turbines, the downstream speed can be expressed by the following expression:

$$u_i = u_0\left[1 - \sqrt{\sum_{i=1}^{N}\left(1 - \frac{u}{u_0}\right)^2}\right] \tag{13}$$

3.3 Cost model

The electricity generated by an aero generator, is a function of the local wind speed. Furthermore, the hub height, the thrust coefficient and the rotor diameter also affects the extracted power.

The total power P extracted from the wind is a function of the local section and wind speed, as shown in the following expression:

$$P = \sum_{i=0}^{N} 0.3{u_i}^3 \tag{14}$$

To calculate the total cost, we modelled the investment cost such a way that only the number of wind turbines must be taken into consideration.

The total cost per year for the entire wind farm can be expressed as follows:

$$\text{cost} = N\left(\frac{2}{3} + \frac{1}{3}e^{-0.00174\,N^2}\right) \tag{15}$$

Where N is the total number of wind turbines.

The objective function that will lead to optimization (minimum cost per unit of energy produced) is expressed as follows:

$$\text{objective function} = \frac{\text{cost}}{P_{\text{total}}} \tag{16}$$

Where P_{total} is the total production, while the cost is calculated as mentioned in equation (15).

Minimize the objective function leads to a solution with the lowest cost of producing wind energy [12].

Wind turbines must be spread over the site to share the best wind between many machines.

3.4 Efficiency Model

Efficiency is determined as a ratio between the amount of energy extracted from the wind farm and the total energy without wake. The numerator represents the actual energy extracted from the rotor of each wind turbine, considering the Betz limit of aerodynamic theory. The wind farm efficiency can be formulated using the equation depending on the number of wind turbines.

Total power produced in wind farm when considering wake effect can be calculated by using equation:

$$P_{Total} = \sum_{i=0}^{N_T} (0.3u_i^3) \tag{17}$$

Equation (15) is used to calculate the wind farm total power without wake effect:

$$P_{WT} = P \times N_T = N_T(0.3u_i^3) \tag{18}$$

Where, *P*, is the rated capacity of each wind turbine.

The overall efficiency of the wind farm is calculated by using equation (19), as follows:

$$\text{Efficiency} = \frac{P_{Total}}{P_{WT}} = \frac{\sum_{i=0}^{N_T}(0.3\times u_i^3)}{N_T(0.3\times u_i^3)} \tag{19}$$

IV. APPLICATION OF GENETIC ALGORITHMS

In this study, we follow [1, 2, 3, 4] study the turbine placement problem on a flat and square farm. The wind farm is divided into 10×10 cells, the width of which is set to be five times that of turbine rotor diameter for safe operations. The center of each cell is the possible position of the turbines. The objective of the optimization is to determine the cells to place turbines so as to minimize the cost per unit energy produced.

The wind turbines placement problem is of discrete type and presents an infinity of optimal solutions, which somehow discards the applicability of optimization methods based on local gradients [1]. Assuming a wind farm described by a 10 x 10 matrix, where each element may contain or not a wind turbine, you can find 2^{100} different configurations, making it impractical to use conventional computers for such problem's analysis.

According to Mosetti et al., for this case, the genetic algorithm is a good tool in the search of the best configuration. This method is able to find an optimal solution to problems of great complexity, eliminating the need of evaluating each individual solution [1].

The optimization algorithms are divided into two main groups: deterministic (based on differential calculus) and random (probabilistic). The deterministic methods are based on the calculation of derivatives or approximations thereof, seeking information from the gradient vector to find the point in which it is annulled, or to find its direction [13].

The random methods use the results of the objective function, which can be difficult to represent, discontinuous, non-differentiable, multimodal (with several minimum and maximum points). These methods look for the optimal value through operating rules of probability in a "randomly oriented" way [13]. One of the main random methods is the genetic algorithm.

Genetic algorithms are probabilistic search algorithms, which are based on the logic of natural selection and the survival of the fittest to commit certain remarkable tasks. Unlike calculus-based methods, genetic algorithms are robust, global, and do not require the existence of derivatives [14].

Since the optimal micro-sitting problem is quite complicated and involves many independent variables, it cannot be solved by traditional gradient-based optimization methods. A genetic algorithm is employed to solve such a problem. In the genetic algorithm, the selection, crossover and mutation are the fundamental operators [14]. The selection operation chooses two parents from the population for crossing. The crossover operator takes two parent solutions to produce a child. The crossover probability Pc is usually between $0.6 \sim 0.9$. The mutation operator introduces new genetic structures into the population by randomly modifying some of its building blocks. It avoids the trap of local minima and maintains diversity in the population. The mutation probability Pm is generally between $0.01 \sim 0.1$. In the genetic algorithm, a few of the best chromosomes should be copied to the new population in case that such individuals can be lost by crossover or mutation operators [14].

After the occurrence of crossover the mutation operator is applied. This operator inverts the values of some genes i.e., a 0 gene can turn to 1 or a 1 gene can turn to 0. This operator is used for increasing the diversity of the chromosomes in a population. Figure 3, adapted from [2], illustrate crossover and mutation operators.

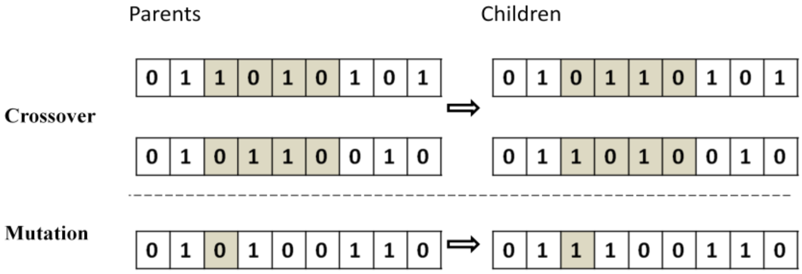


FIGURE 3. Crossover and Mutation Operators

In the present study, the field is described by a code matrix composed of m by n "zeros" and "ones", where 0 simply means a space without the presence turbine 1 and a wind turbine, as shown in figure 4.

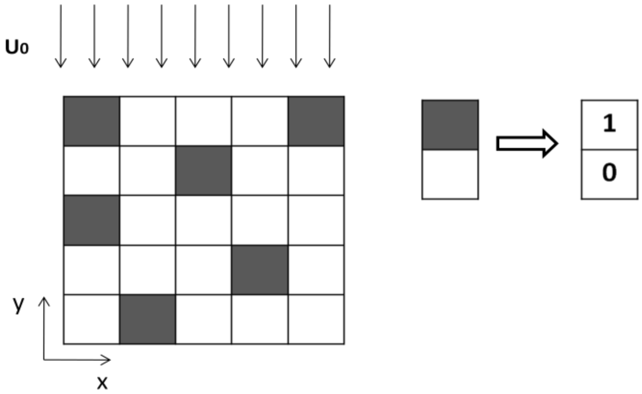


FIGURE 4. Codification Method

V. NUMERICAL PROCEDURE

The code is attached to the WFOAG optimization tool by genetic algorithm. The flowchart in figure 5 explains the process through which WFOAG is used as the objective function, generating the necessary results to evaluate individuals created. Basically, the optimization process is divided in three stages: Pre-processing (Initialization), Processing (genetic algorithm) and Post processing (a result evaluation).

5.1 Pre-processing

In the first stage, are specified the optimization parameters as: Number of input variables: for the proposed problem, the only variable input is the matrix position (layout of the wind farm); Size of initial population: the total number of solutions that are generated randomly for the first generation; Restrictions: In order to avoid unfeasible evaluations of individuals, as restrictions are imposed minimum production or efficiency; Optimization criteria: the optimization criteria include the maximum number of iterations (called generations), the probability of crossover, mutation and selection, and optimization method.

5.2 Processing

After the initialization process, starting from a given initial population, the fitting of each individual is evaluated by the objective function (WFOAG), and by the best individuals, the next generation will be designed. This new population is obtained through crossover and mutation among individuals with higher fitting in random regions.

In the next step optimization criteria are checked if they are satisfied or not. When the optimization criteria are not met, all the solutions are ranked based on their objective function values. A solution with small objective function value is better as its cost per unit power is smaller and is placed before other solutions with larger objective function value. For example, a solution with objective function value of 0.02 is placed before a solution with objective function value of 0.03.

After ranking is completed, some solutions are selected based on which new solutions are created (reproduced). This selection of solutions is affected by the ranking done in previous step and a solution with good ranking has a better chance of being selected. New solutions are created but some solutions are copied from original set of solutions to the new set of solutions. These selected few solutions are one of the best in terms of the ranking and are called elite count.

The next step before new set of solutions (new population) is ready is called Mutation. In this step some random changes are made in few solutions. This step is very important as it helps in maintaining diversity in the solution set. This new solution set is analyzed by WFOAG and this iterative procedure continues until one of the optimization criteria is satisfied. In the simulation, the type of selection is set as (Stochastic uniform), the type of crossover is set as (scattered) with the crossover probability Pc = 0.8, and the type of mutation set as (Uniform) with the mutation probability Pm = 0.05.

5.3 Post-processing

Just the once computations have stopped, the results are exported from the WFOAG and the exported structure is saved to a file for later use. The coordinates of all the wind turbines are saved in a separate variable and analyzed to determine the power produced. The layout can be plotted as per the requirement.

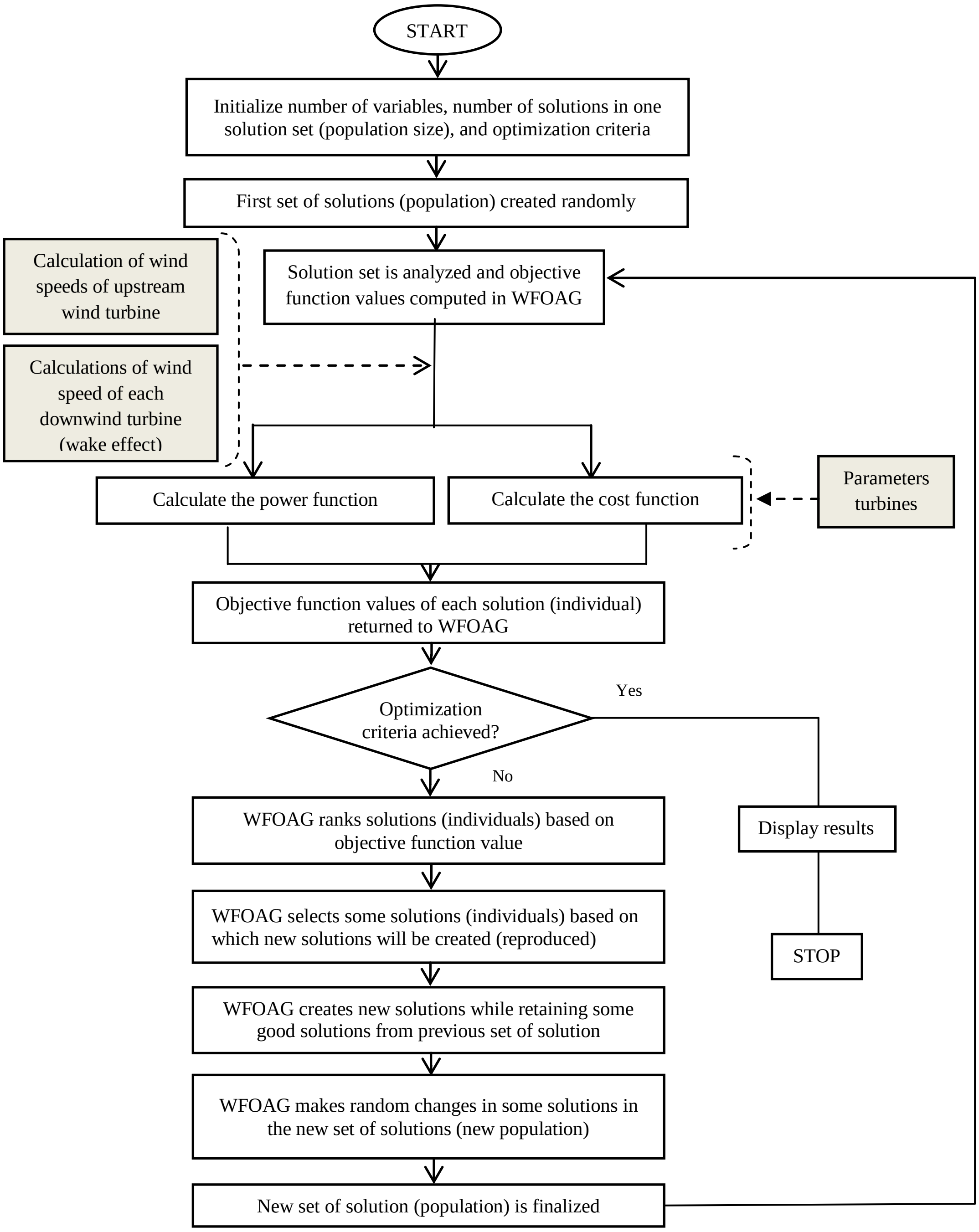


FIGURE 5. Flowchart Describing the Optimization Process

VI. RESULTS AND DISCUSSIONS

6.1 Influence of wake effect on wind speeds of each wind turbine

In order to analyze how wind speeds of each turbine are affected by wakes, two different scenarios have been simulated. The first, a wind farm composed of 16 wind turbines (4X4) is presented. The y-axis is fixed to 0° which it is assumed to be coincident with the prevailing wind direction. The wind farm layout, as well as the wake effect caused by a particular incoming wind direction of 30°, is shown in Fig. 6(a). The distance between two nearby wind turbines in axis y (Dist_y) is 7 rotor diameters (D) and 5 rotor diameters (D) in axis x (Dist_x).

In Fig. 6 (b), the wind speed of each wind turbine is shown. As expected, the wind speeds obtained by means of simulation are consistent with the above mentioned. The average wind speed for the entire wind farm is 8 m/s, which is relatively high, although lower than full load, and therefore the thrust coefficient has not dropped significantly as at high wind speeds.

(a) (b)

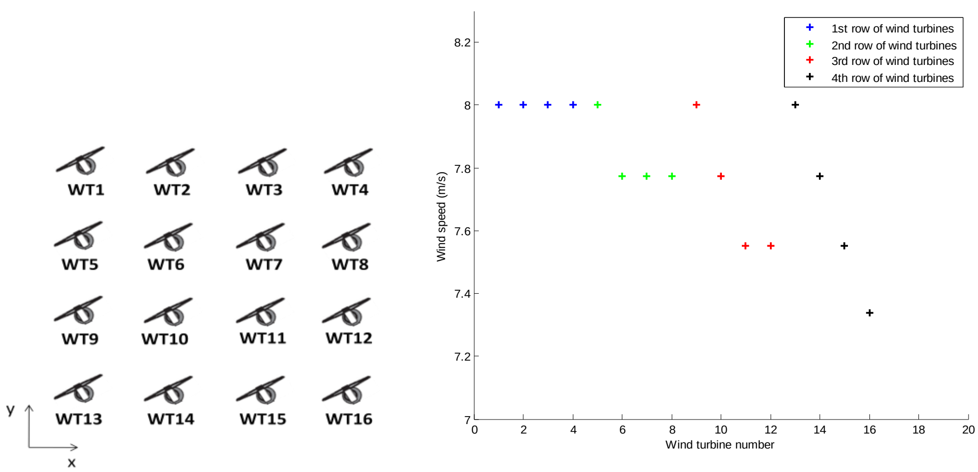


FIGURE 6. (a) Wake Decay for A 16 Wind Turbine Array (4x4) Spaced 7d (Dist_Y) And 5d (Dist_X) When The Prevailing Wind Direction Is 30°. (b) Wind Speeds of Each Turbine.

The second wind farm scenario consists of 16 wind turbines laid, out in 4 rows with a spacing of about 5 rotor diameters (D) between and along rows (Dist_x and Dist_y). The incoming wind direction is coincident with the prevailing wind direction, that is, 0° (see Fig. 7(a)).

(a) (b)

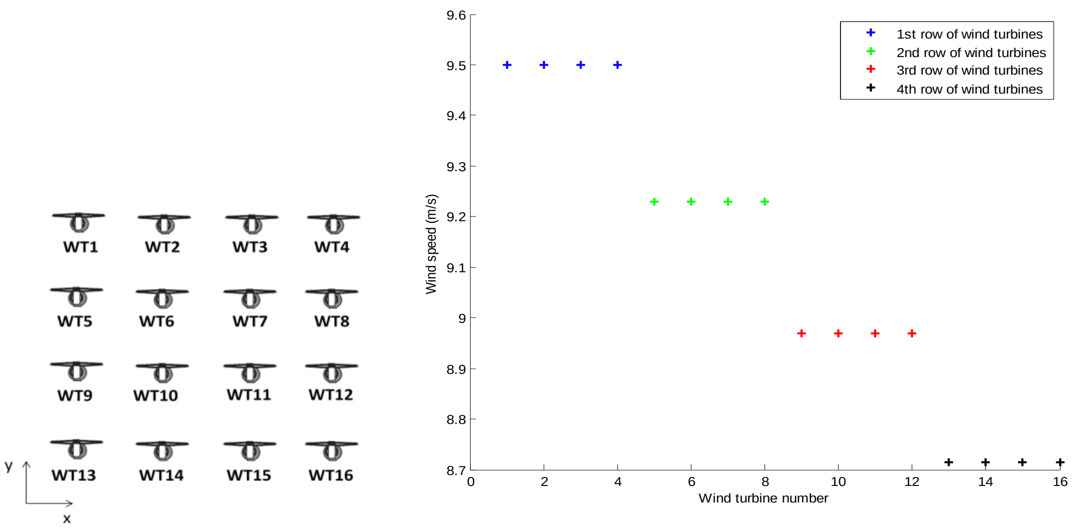


FIGURE 7. (a) Wake Decay For A 16 Wind Turbine Array (4x4) Spaced 5d (Dist_Y) And 5d (Dist_X) When The Prevailing Incoming Wind Direction Is 0°. (b) Wind Speeds of Each Turbine.

In this case, the rows 2, 3and 4 are affected by wakes. The wind turbines located in the second row (green WTs) are affected by a single wake, whereas, the turbines in the third and fourth row are affected by multiple wakes.

For both scenarios (30° and 0°), the entrainment constant k is 0.04. As in the previous case, the wind speeds of each wind turbine are depicted in Fig. 7(b) and are consistent with the wind farm layout of Fig. 7(a). The average wind speed for the entire wind farm is 9.5 m/s.

6.2 Comparison to previously published wind farm optimization cases

In a way to verify the WFOAG performance, some simulations were done and the results were compared with other authors' works [1, 2, 3, 4]. These works were chosen because they use the same parameters used by Mosetti et al. model as well as Jensen's wake model [9] and probabilistic algorithms as optimization tool, guaranteeing control and reliability of results.

Without loss of generality, we suppose the wind speed distribution in both cases satisfies the Weibull function. The shape parameter of the Weibull function is set to k = 2, which represents a typical wind condition for turbine operations.

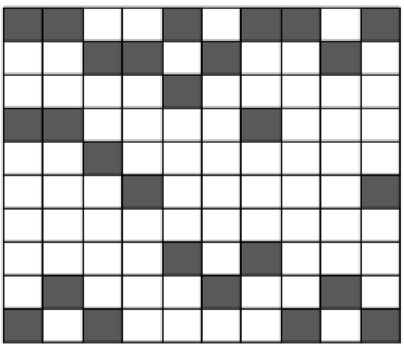
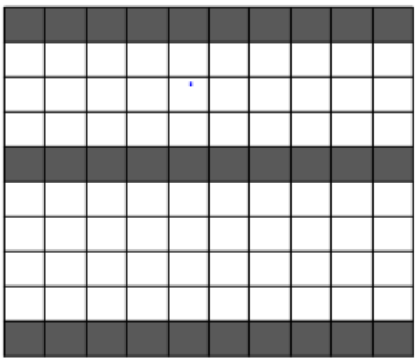
The scale parameter of the function is calculated as c = 13.54. The surface roughness of the wind farm is $z_0 = 0.3m$. The parameters of the wind turbine are shown in Table 2.

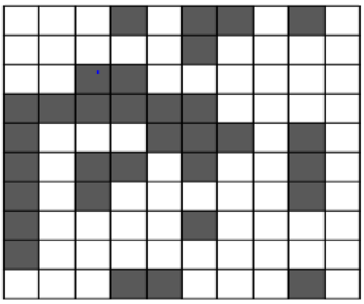
TABLE 2
CARACTÉRISTIQUES OF TURBINES

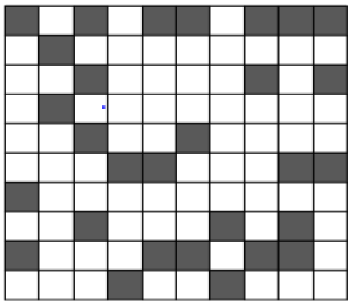
Description	Parameter	value
Hub height	z	60 m
Radius of the rotor	r_r	40 m
Thrust coefficient	C_t	0.88

In order to estimate the optimal number of wind turbines and for comparative purposes we will take the following basic conditions: uniform wind direction and speed steady wind of 12 m / s.

TABLE 3
WFOAG RESULTS FOR COMPARISON WITH PREVIOUS STUDIES

<table>
<tr><td>Mosetti et al.
Number of turbines 26
Total power 12921 KW/ year
objective function 0.0016197
Efficiency 95.5%</td><td>Grady et al.
Number of turbines 30
Total power 14764KW/ year
objective function 0.0015436
Efficiency 94.6%</td><td>Emami
Number of turbines 26
Total power 12921KW/ year
objective function -
Efficiency 95.5%</td></tr>
<tr><td></td><td colspan="2"></td></tr>
<tr><td>Marmidis
Number of turbines 32
Total power 13467 KW/ year
objective function -
Efficiency 80.9%</td><td colspan="2">Present results
Number of turbines 29
Total power 14664 KW/ year
objective function 0.0014710
Efficiency 95.4%</td></tr>
</table>





This case has been discussed in detail in [1, 2, 3] where different approaches were used. Choosing this case study was performed for comparison. In this case, turbines affect each other. This makes it difficult to place the turbines through the experience. To describe the placement of a wind farm, it is necessary to evaluate parameters: layout Efficiency (%) and electricity production (kWh).To calculate this parameter a code has been developed which considers the wake effect as the main influence on the decline in production of a wind farm. This code will be used as the objective function of the optimization algorithm, and will provide the necessary parameters for comparison and selection of the best layouts.

The input parameters are the velocity of the not disturbed flow upwind turbine, the rotor diameter of wind turbines, the hub height, the terrain roughness and the power curve with values of the thrust coefficient and power turbine velocity for any wind within the operating range. This code considers possible interactions between wakes. A wind turbine can be influenced by more than one wake from upwind turbines, plus there is the possibility of overlap between wakes.

Some simplifying assumptions were considered in the code developing. They are: all the turbines in the wind farm are equal, i.e. have the same height of the cube, the same rotor diameter, same number of blades and the same power curve, the ground location of the wind farm is perfectly flat, uniform roughness, the turbines are arranged in a matrix, a result for a single value of velocity and direction.

The layouts proposed by these authors were simulated in WFOAG to obtain the results for comparison, making it as impartial as possible. Then a different wind farm configuration was inserted in the WFOAG (under the same conditions used by Mosetti et al.) to be optimized. The aim of this process was to verify the capacity of the WFOAG to achieve a layout performance near or higher than the proposed by the authors. The simulated layouts are illustrated in Table 3.

VII. CONCLUSION

The placement of wind turbines is an initial step in the wind farm design and forms the foundation for the efficient operation of the farm. At present, empirical schemes are commonly adopted. As the wind condition becomes complicated, systematical approaches such as genetic algorithms are needed to reach an optimal or suboptimal design. This paper further previous research on genetic algorithm placement by incorporating more appropriate models of wind speed distributions and turbine power curves. Simulation results indicate that the new genetic-algorithm scheme can improve wind farm performance, which expands more computation due to complicated models. It is of importance to study more realistic situations, for example, to use a more relevant wind turbines probably with pitch control systems, to use a cost model including cabling, to study relatively complex terrain layouts.

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