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Optimization of Wind Farm Layout Using Genetic Algorithm

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1. Abstract
This paper describes the development of a layout optimization algorithm of wind farms. Given the wind's condition, and the combination of the characteristics and number of wind turbines, it determines the optimal position of each turbine, so that the wind farm's efficiency is maximized. First, a code is developed in MATLAB for wind farm energy production calculation. This code is based on a simple wake model that considers the cumulative impact of multiple shadowing and thrust coefficient curve C_T. Then, the optimization algorithm developed in modeFRONTIER is demonstrated. Lastly, tests and verifications are performed and its results are compared with the commercial software WindFarmer and previous studies.
2. Keywords: Wind Farm, Wake effect, Optimization, Genetic Algorithm, modeFRONTIER.

3. Introduction
A big challenge faced by wind energy generating agents is to increase production capacity and lower implementation cost. In this context, for electricity generation by wind power, it is necessary to conduct studies and evaluations of factors that may influence the production potential of a wind farm.
Due to limited production capacity of a single wind turbine, the energy available in the wind is extracted on a large scale by installing a large amount of wind turbines, forming the so-called wind farms. This arrangement is used to achieve greater energy production and reduce costs of installation, operation and maintenance [1].
During the planning process of a wind farm, an important aspect to be considered is the most efficient use of the available area. However, an increase on the number of wind turbines leads to a smaller distance between each turbine, which may induce a scenario in which one turbine influences negatively the others, through a process referred as *wake effect.* This negative effect reduces the global production of the wind farm.
Wind turbines extract energy from the wind to produce electricity. Therefore, the *downwind* will have less available energy than the *upwind.* Consequently, the turbine's downwind will have its velocity lowered and the flow will be turbulent, composing the so called wake of the turbine. The two main effects of it are a reduction in the wind velocity, which in turn reduces the energy production of wind farm and an increase in the turbulence of the wind, potentially increasing the dynamic mechanical loading on downwind turbines [2].
This work presents the development of the production calculation, implemented in MATLAB, considering the wake iteration and C_T curve. Then, optimization methods are explored and the optimization algorithm developed in modeFRONTIER is demonstrated. Lastly, tests and verifications are performed and its results are compared with the commercial software WindFarmer and previous studies.

4. Previous Studies
One of the first approaches towards optimizing efficiency in wind farms was to set minimum distances between turbines. This method was proven insufficient since it does not address efficiently the overall wind farm's potential for generating energy[3].
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 [8], 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. developed a work in the same research line [9]. However, their optimization process was restricted to only a portion of the evaluated land, and then their results were spread throughout the rest of the area. Another work was developed by Marmidis et al. in 2008 [3], which used a different optimization method, the Monte Carlo method.
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 considerations have been adopted, such as the interaction between wakes, proposed by Sethi et al. in 2011 [6], and the use of C_T curve for calculating the energy output of a wind farm.

5. Wind Farm Model

The wake model used is the one proposed by Jensen (1983) [4], which describes, in a simple manner, the wind behavior of a wake. This model considers the wake after the turbine as being a turbulent one, and its velocity as a function of the downwind distance of the wind turbine, and it is assumed that the expansion of the wake diameter follows a linear pattern [4], as seen in Figure 1.

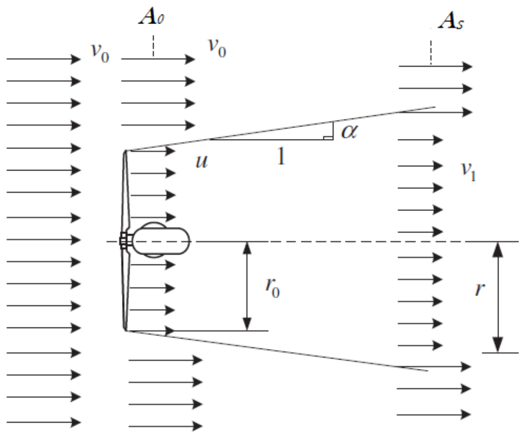


Figure 1: Schematic of Jensen's wake model

This model was chosen based on a comparison of different wake models, presented in Ref. [5], which shown no big difference, in terms of accuracy, between the simplified and sophisticated methods.

5.1. Jensens model for a single wake

Assuming that momentum is conserved in the wake, the wind velocity v_1 of a downwind wind turbine is given by

$$v_1 = v_0 + v_0\left(\sqrt{1 - C_T} - 1\right)\left(\frac{r_0}{r(x)}\right)^2 \tag{1}$$

where v_0 is the free-flow velocity,v_1 is the wind velocity of the downstream wake, distant by an amount of x to the wind turbine, r_0 is the wind turbine rotor radius, r is the downstream wake radius, distant by an amount of x from the wind turbine and C_T is the turbine thrust coefficient, that can be calculated by

$$C_T = 4\alpha(1 - \alpha) \tag{2}$$

The dimensionless constant α tells how fast the belt will expand with "x" distance. This constant can take different values depending on the characteristics of the local terrain and weather conditions, and it is given by

$$\alpha = \frac{1}{2ln\left(\frac{h}{z_0}\right)} \tag{3}$$

where "h" represents the hub height, and z_0 is the terrain roughness.

Since the expansion of the wake is linear, the path described by the wind that crossed the turbine rotor is represented by a cone. The radius of the cone (wake) is given by the following expression

$$r(x) = r_0 + \alpha x \tag{4}$$

5.2. Multiple wake model

In order to obtain a usual result for wind farms with many turbines, the effects of various individual wakes must be combined into those of a single wake. However, the influence of each wake in the wind turbine must be analyzed separately by calculating the shaded area. This shading is a measure of the overlap between the area of the circular section of the wake and the turbine area that suffers the action of this wake, as illustrated in Figure 2, adapted from [2].

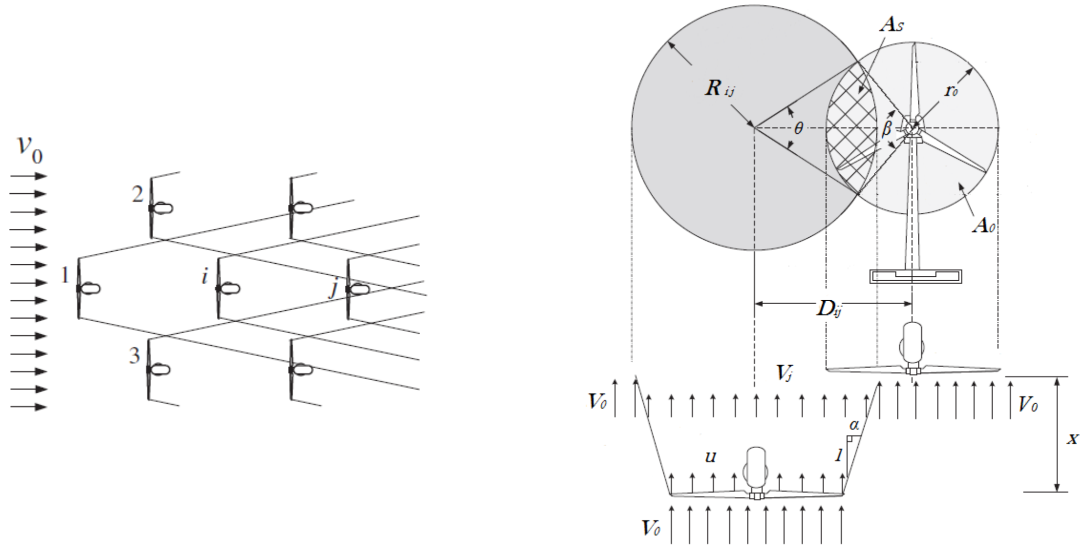


Figure 2: (a) multiple wake condition; (b) schematic of partial shadowing

There are three possibilities for shadowing: full shadowing, partial shadowing and no shadowing. For a fully shadowed turbine the input velocity is equal to the wake velocity that shadows it. For the situation of no shadowing, the input velocity is the velocity of the available wind in the environment.

If the wind turbine rotors have the same diameter, the area shadowed by the turbine can be calculated using basic trigonometric relationships that results in the equations below.

$$A_S = r^2\big(\theta - (sen\theta cos\theta)\big) + R^2\big(\beta - (sen\beta cos\beta)\big) \tag{5}$$

$$\theta = cos^{-1}\left(\frac{r^2 + D_{ij}^2 - R_{ij}^2}{2D_{ij}r}\right) \tag{6}$$

$$\beta = cos^{-1}\left(\frac{R_{ij}^2 + D_{ij}^2 - r^2}{2D_{ij}R_{ij}}\right) \tag{7}$$

where A_S is the area shadowed by the upwind turbine, "θ" is the angle between the center of the circle corresponding to the wake and the points of intersection between said circumference and the circumference corresponding to the area swept by the wind turbine, β is the angle between the center of the circle corresponding to the swept area and the point of intersection between this circumference and the circumference of the wake, as seen in Figure 2.

The wake influence in the input velocity in a wind turbine is modeled differently when one has an overlapping of wakes [6]. To consider this effect, the model of Sethi [6], inserts a weighting (dependent of the shadowed area and the diameter of the wake at the position of the shadowed wind turbine) in the model proposed by Jensen [4], as shown in equation 8.

$$V_j = V_0\left(1 - C_r\frac{D^2}{A_0}\left(\frac{x_{ij}}{2R_{ij}^2}\right)\right) \tag{8}$$

$$C_r = 1 - \sqrt{1 - C_T} \tag{9}$$

where V_j is the resulting input velocity in the turbine j,V_0 is the free-flow velocity, D is the rotor diameter, A_0 is the rotor swept area, R_{ij} is the wake radius performed by the "i" wind turbine on a "j" wind turbine, x_{ij} is a factor that depends on the shadowing condition of turbine j, which equal to 1 when fully shadowed and equal to the shadowed areas sum when partially shadowed.

6. Optimization Algorithm

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 [7]. 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 [7]. One of the main

random methods is the genetic algorithm.
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 [8]. 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 [9].
Genetic algorithms are probabilistic search algorithms, which are based on the logic of natural selection. This algorithm uses a data structure similar to a chromosome for solving problems. Using genetic operations inspired in evolutionary biology and heredity (such as selection, crossover and mutation), it performs a targeted search, even though mostly random. Genetic algorithms are not a simply random search, because they are based on data obtained from individuals of previous generations to find "best fitting" individuals [10]. As in the natural process of reproduction, the genetic information contained in a chromosome strip of two individuals is used to create the genetic code of a new individual. The evolution and adaptation of species are guaranteed because the best individual has higher probability to survive and reproduce [8].
During the genetic algorithm optimization process, three different operators are applied: selection, crossover and mutation. The main role of the selection process is to enable the information contained in the good chromosomes to survive in the next generation, based on the chromosome fitness: if it doesn't fit, it is discarded. The crossover operator is applied in a pair of chromosomes, called parent chromosomes, which will generate two new chromosomes, the son chromosomes. Each parent chromosome has his strip cut into any position of its length, being divided into two parts that will be exchanged between them. When the crossover does not happen, the children will have the same characteristics of parents preserving some solutions [10]. 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 [9], illustrates crossover and mutation operators.

	Parents	Children
Crossover:	0 0 1 0 1 1 0 0 1 1	0 0 1 0 0 0 1 0 1 1
	1 1 1 0 0 0 1 0 1 0	1 1 1 0 1 1 0 0 1 0
Mutation:	1 0 0 0 1 1 1 1 1 0	1 0 1 0 1 1 1 1 0 0

Figure 3: Crossover and mutation operators

7. Numerical procedure

7.1 Production Calculation Algorithm (PCA)
To define the layout of a wind farm, it is necessary to evaluate parameters to point the yield of the proposed configuration. These parameters can be: electricity production (kWh) and layout Efficiency (%). To calculate this parameter a MATLAB code has been developed – Production Calculation Algorithm (PCA) - 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, e.g. 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 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.

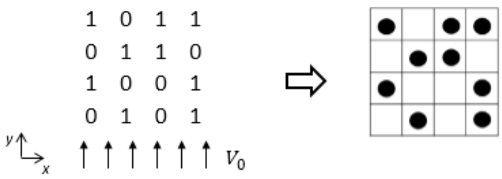


Figure 4: Code matrix to wind farm layout

7.2 Production Calculation and Optimization Algorithm

The code is attached to the PCA optimization tool by genetic algorithm / modeFRONTIER. The PCA is used as the objective function within the modeFRONTIER, generating the necessary results to evaluate individuals created. Basically, the optimization process is divided in three stages: Pre-processing (or startup), Processing (or solution) (genetic algorithm) and Post processing (a result evaluation).

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.

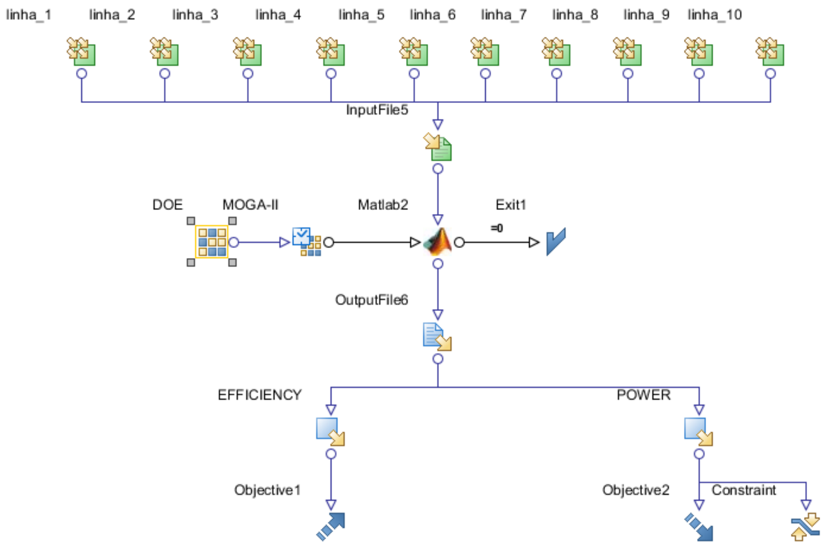


Figure 5: modeFRONTIER algorithm scheme

In the second stage, starting from a given initial population, the fitting of each individual is evaluated by the objective function (PCA), 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. Both operations will occur with a certain probability: from 0.6 to 0.9 for the crossover and from 0.01 to 0.05 for the mutation [11]. The crossing has a higher probability to occur because it is the most responsible for the "local evolution" of the population, while the mutation rarely occurs, because it is responsible for the random introduction of new features in the population preventing premature convergence of the optimization optimum local [8].

It may be noted that this optimization method searches for the best population and not directly by the best individual. Therefore, the best solution may be found in earlier stages of evolution. However, with increasing fitting of the population, the fittest individual of the population will probably be more developed [8].

In order to choose the parameters that best suited the study in case, tests were conducted with key optimization methods available in modeFRONTIER. The criteria used for evaluation were: variety of operators of reproduction, adequacy of results and ease of convergence. The method chosen was the Multiobjective Genetic Algorithm II (MOGA-II).

After selecting the method, a calibration was done by choosing the best operators playback rates. To this end, tests were conducted with several different configurations of these operators always for the same condition. The values of the probability of occurrence of genetic operators were: 0.8 for crossover, 0.01 to 0.07 for mutation and selection. The modeFRONTIER algorithm scheme is shown in figure 5.

8. Results

The results obtained using the developed algorithms, explained in the topics 7.1 and 7.2, are presented and compared to results of previous studies [3, 8, 9] and the software WindFarmer. This software is a good tool for comparison because it has validated data through measurements in wind farms already in operation. As comparison parameters, the number of turbines, the total power, efficiency and capacity factor were chosen.

8.1. Verification for wind farm with N turbines in a studied arrangement

At this stage the objective was to evaluate the reliability of PCA-generated results, as this program is the objective function of the optimization algorithm developed and if their results are not consistent, the optimization process will fail. Another analyzed relevant factor was the influence of C_T used in the calculation of the resulting velocity according to equation 8 and 9. In previous works [8, 9, 12] this variable was considered constant.

8.1.1. Verification of results obtained in PCA

Considering the data availability, the configuration proposed by Mosetti et al., 1994, was chosen for simulation and results comparison, where wind velocity and direction are constants. Table 1 and Figure 6 shows the input parameters used.

Table 1: Input parameters used by Mosseti et al.

Input parameters	
Roughness (Z_0)	0,3
Wind velocity in free flow (V_0)	12 m/s
Hub height (h)	60 m
Rotor diameter (D):	40 m
Wind Farm dimension:	2000X2000 m
C_T	0,88

Initially, this wind farm layout was simulated in WindFarmer and its results were collected for comparison with the results obtained by Mosetti et al. [8] The purpose of this simulation is to compare the wake model used by the concerned author, and by the present work (Jensen's model) with the computational model used by software WindFarmer (Ainslie's model). As WindFarmer does not work with arrays, but with geographic coordinates, the placement of wind turbines was done manually, stating the coordinates of each turbine, so that it truly describes the configuration matrix proposed by Mosetti et al [8].

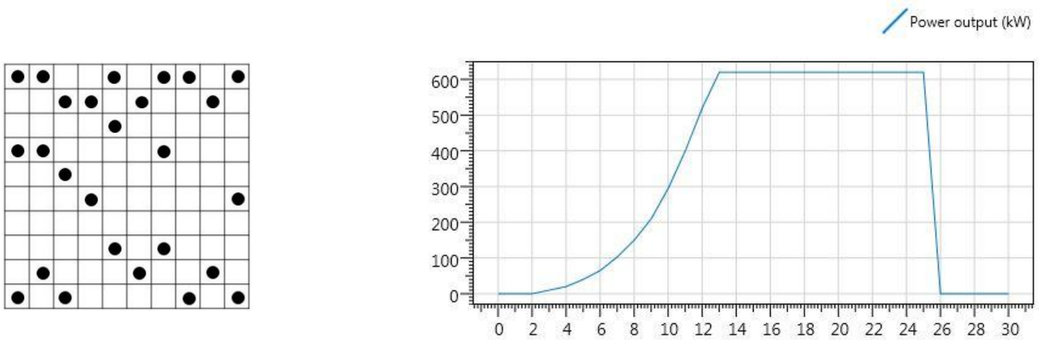


Figure 6: Wind farm layout and turbine power curve used by Mosetti et al.

Later, this layout was simulated in PCA and its results are compared with those obtained in the work of Mosetti et al. and in WindFarmer as well. Table 2 presents the results obtained.

Table 2: Results for the wind farm layout proposed by Mosetti et al.

	Number of turbines	Total Power[kW]	Efficiency [%]	Capacity factor [%]
Mosetti et al.	25	12375	95,0	79,8
PCA	26	12921	95,5	80,0
WindFarmer	26	13127	97,0	81,4

Once the data was successfully obtained, it was possible to infer that the model proposed by Jensen [4] is a good approximation for describing the wake effect, since the results obtained with this model acceptably approached the results generated in WindFarmer, which uses Ainslie's model into its calculations. The difference between the two models occurs mainly by how the wake profile is described, as the Jensen's model overestimates the wind velocity deficit.
Comparing the total power, efficiency and capacity factor, it was observed that the PCA data has a small difference compared with WindFarmer, not exceeding 1.7%, showing that the calculation methodology developed for the PCA is reliable and serves as a good initial estimate. Thus, we conclude that the PCA is a tool that generates reliable data, being adequate to be used as an objective function in optimization algorithm.

8.1.2. Influence of C_T in energetic production calculation
During the development of PCA, it was noted that the C_T factor had a great variation with velocity increases. As this parameter is used in the wake calculation and the park production is influenced by the wake that each turbine produces, such parameter cannot be considered constant. With this, it was decided to also use the curve that represents the CT of a turbine as an input value in the PCA calculations and do some analysis of the results generated to see how different the results would be.
For this test, it was inserted the C_T curve of the turbine used in the work of Mosetti et al. [8] into PCA and WindFarmer, and the results compared with testing done in 8.1.1 where C_T was considered constant and equal to 0.88. Table 3 shows the results.

Table 3: C_T test results

	Number of turbines	Total Power[kW]	Efficiency [%]	Capacity factor [%]
Mosetti et al.	25	12375	95,0	79,8
PCA$_{\text{Constant}}$	26	12921	95,5	80,0
PCA$_{\text{Curve}}$	26	13316	98,5	82,6
WF$_{\text{Constant}}$	26	13127	97,3	81,4
WF$_{\text{Curve}}$	26	13242	99,0	82,1

Analyzing the results obtained, it was found that the C_T is a parameter that directly influences the wind farm production. For the studied situation, the use of C_T curve resulted in an increase of about 3% in the total production of the park. Thus, considering it a constant would cause an underestimation of the potential production of a wind farm.
In order to better visualize the influence of this parameter, a graph was generated, in which it was calculated the production of a wind turbine under a fully shadowed state, varying its distance from the windward turbine. This graph is shown in Figure 7.

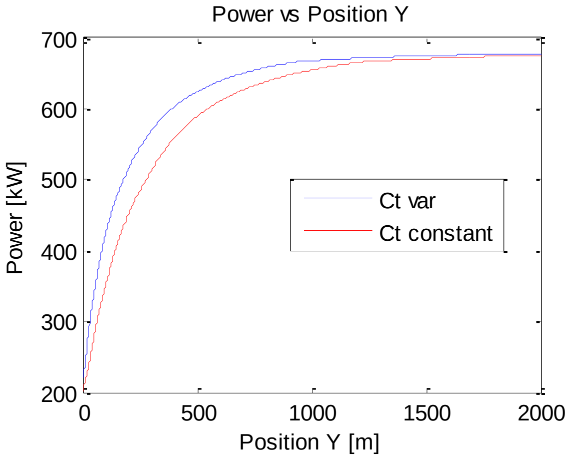


Figure 7: Influence of the C_T curve

From the graph, for example, one realizes that a wind turbine with a constant C_T 400 meters away from a downwind turbine presents a significant drop in its production, approximately 8%, compared to its production if the C_T curve was considered.

8.2 Energetic production for n wind turbines in optimized arrangement

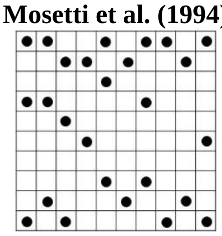
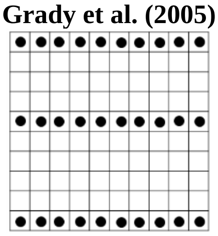
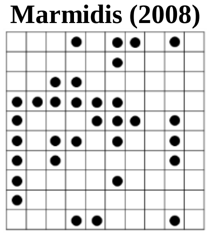
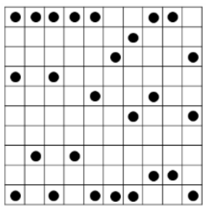
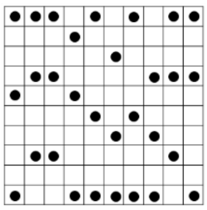
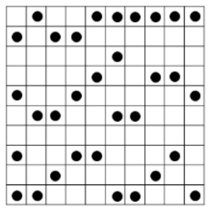
This step was designed to verify the quality of the optimization process. The suitability of the obtained results and the ease of convergence were considered as parameters for certifying the quality of the process. For this end, two simulations were made in which the first used the parameters proposed by Mosetti et al. and the second utilized the parameters that better approached the global scenario of wind generation.

8.2.1. Random layout optimization and comparison with other works

In a way to verify the PCOA performance, some simulations were done and the results were compared with other authors' works [3, 8, 9]. These works were chosen because they use the same parameters used by Mosetti et al. model as well as Jensen's wake model [4] and probabilistic algorithms as optimization tool, guaranteeing control and reliability of results.

The layouts proposed by these authors were simulated in PCA to obtain the results for comparison, making it as impartial as possible. Then a different wind farm configuration was inserted in the PCOA (under the same conditions used by Mosetti et al.) to be optimized. The aim of this process was to verify the capacity of the PCOA to achieve a layout performance near or higher than the proposed by the authors. The simulated layouts are illustrated in Table 4, noting that the wind blows on the positive y-axis.

Table 4: PCOA results for comparison with previous studies

Mosetti et al. (1994)	**Grady et al. (2005)**	**Marmidis (2008)**
		
Number of turbines: 26	Number of turbines: 30	Number of turbines: 32
Total power [kW]: 12921	Total power[kW]: 14764	Total power [kW]: 13467
Efficiency [%]: 95,5	Efficiency [%]: 94,6	Efficiency [%]: 80,9
PCOA	**PCOA**	**PCOA**
		
Number of turbines: 26	Number of turbines: 30	Number of turbines: 32
Total power [kW]: 12985	Total power [kW]: 14790	Total power [kW]: 15574
Efficiency [%]: 96,0	Efficiency [%]: 94,8	Efficiency [%]: 93,6

From the results shown in Table 4, some conclusions can be made. First, it was noted that the methodology used in this work, in light of the closeness between the results and those reported by the authors, was of guaranteed quality.

Furthermore, the effectiveness of the algorithm developed in this work, as well as the tool - the software modeFRONTIER - used for the development of the algorithm were noted. This was verified due to the closeness of the results compared to the work of Mosetti et al. [8] and Grady et al. [9], considering that these two have used genetic algorithm for optimization.

Finally, the suitability of the genetic algorithm to the situation studied was verified. Comparing PCOA results with those obtained by Marmidis et al., there is a significant increase in efficiency and in total production, of about 15%. This difference is probably related to the optimization method used because Marmidis et al. uses the Monte Carlo method and the present work uses the genetic algorithm, which proved to more effective.

8.2.2. Random optimization with arbitrated parameters

As a final test to verify the PCOA, a simulation optimization has been made with technical data closer to the current context of wind energy generation. Also, this simulation was reproduced in WindFarmer software to check the closeness of the results obtained by PCOA with a highly renowned commercial software on the market.

For this test, firstly data relating to wind turbine wind and land are acquired. The data were acquired in the turbine manufacturer's website and these are of the Vestas V90 - 3.0 MW considerably used on the world stage of wind energy generation. The wind data was estimated using the Atlas of Brazilian Wind Potential [13] and was chosen to Northeastern Brazil where the average wind is around 9.5 m / s. The surface roughness was obtained through a table of roughness, which was defined as more suitable to the terrain seen in region chosen roughness of 0.3 Z_0.

Subsequently, certain parameters were arbitrary, such as the number of wind turbines to be installed and dimensions of the ground. In order to keep the standard adopted in previous simulations, a plot of 2000 meters wide by 2000 meters long was chosen. As for the number of turbines, the amount of 30 machines was determined. Once the parameters were defined, they were inserted into PCOA and WindFarmer. Then the optimization process was started up and the results obtained are shown in Table 5.

Table 5: PCOA x WindFarmer

	Number of turbines	Total Power[kW]	Efficiency [%]	Capacity factor [%]
PCOA$_{10X10}$	30	54932	87,1	61,0
WindFarmer	30	55936	82,5	62,1

Evaluating the results of this process it is possible to notice a difference between the values. This is primarily due to the greater flexibility of positioning of wind turbines in the program WindFarmer that, unlike PCOA, has no restriction on the positioning of wind turbines. Another factor is the modeling of the wake effect used by WindFarmer, which allows for a better description compared to the model used in the PCOA.

In order to confirm the influence of the flexibility of positioning of wind turbines in performance optimization, a simulation was performed in which the possibility of allocation of wind turbines was decreased. For the case compared with the WindFarmer in Table 5, a 10X10 matrix was used and to test this theory confirmation a 8x8 matrix and a 12x12 matrix were used, that is, the first case has 100 possible sites of allocation of the wind turbines, as second shows only 64 places, and the third, 144. Table 6 shows that the results confirm the hypothesis suggested and Figure 8 shows a graph of efficiency by size of the matrix (number of rows and columns of the matrix) showing the evolution. The points found are shown in the graph by triangular elements. The red curve is a power adjustment done by the tool CFTool MATLAB.

Table 6: Different grid size results

	Number of turbines	Total Power[kW]	Efficiency [%]	Capacity factor [%]
PCOA$_{8X8}$	30	53775	85,3	59,7
PCOA$_{10X10}$	30	54932	87,1	61,0
PCOA$_{12X12}$	30	55395	87,9	61,6

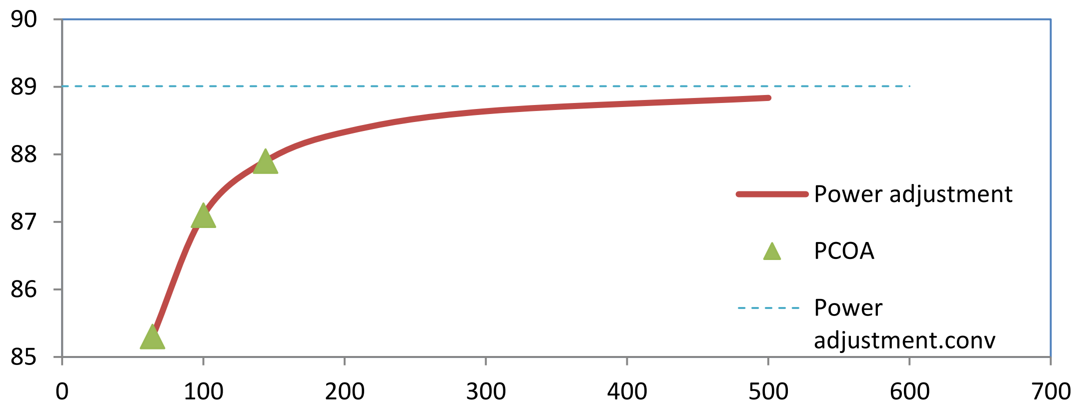


Figure 8: Grid size analysis curve

It can be seen that convergence would occur for a optimizing value of 89.1%, showing that other factors also influence the optimization. Despite the differences found in the results of the two programs - about 1.8% lower in the PCOA - this test showed that the PCOA is a good tool for initial estimates of production on a wind farm to be deployed.

9. Conclusions

From the studies and procedures carried out in this paper, the expressivity of the wake effect in defining the wind farms layout was confirmed. Furthermore the developed algorithm was proven to be a good tool for wind farm optimization, serving as initial estimate for wind farm projects. From the results obtained, it was concluded that the genetic algorithm optimization method is simple and efficient, able to generate excellent results for the discussed problem.

If improved, the program created in this paper may predict the performance of a wind farm with higher reliability. More accurate results can be obtained by introducing the possibility of using varying wind conditions (velocity and direction), with the inclusion of topographic features and use of a wind farm modeling far more complex.

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