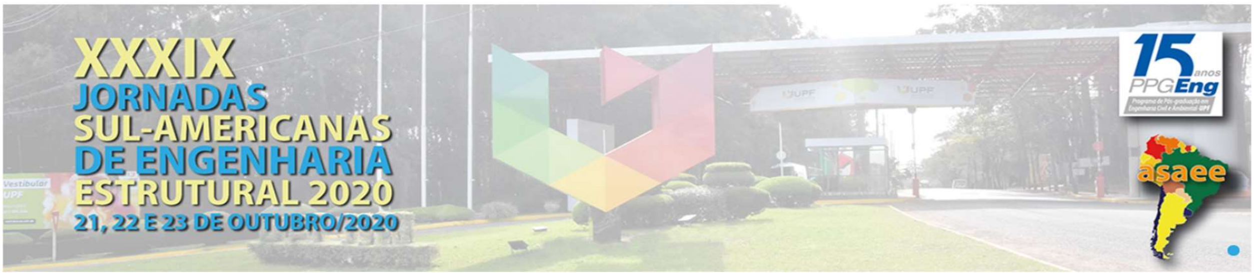

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OTIMIZAÇÃO DE MICROSITING DE PARQUES EÓLICOS: UMA ABORDAGEM METAHEURISTICA

WIND FARM *MICROSITING* OPTIMIZATION: A METAHEURISTIC APPROACH

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Resumo

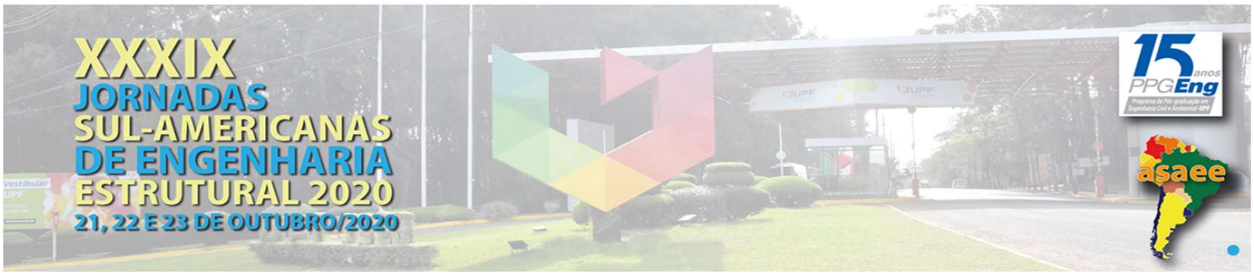
A energia eólica está cada vez mais participando da matriz energética dos países como uma fonte alternativa de energia sustentável. Parques eólicos são a forma racional de gerar este tipo de energia e o Brasil é um país que tem um grande potencial para ser explorado. Neste trabalho, o layout de parques eólicos é otimizado de forma a maximizar a produção energética que depende das condições de vento da região onde está instalado o empreendimento, bem como o número de aerogeradores disponíveis e os limites geográficos para instalação dos mesmos. A otimização é baseada em um algoritmo metaheurístico, QPSO, uma vez que, em geral, o posicionamento dos aerogeradores não pode ser feito de forma contínua, mas de forma discreta em função de distâncias mínimas recomendadas entre as torres. O algoritmo QPSO é testado em uma avaliação nomeada pela literatura como Caso Ideal. A função objetivo do problema é alcançar o aumento da eficiência em geração energética decorrente dos *micrositings* para realizar uma comparação com os resultados relatados na literatura. Para o caso avaliado, o QPSO foi capaz de encontrar soluções mais eficientes que outras abordagens, mesmo com maior dispersão entre todas soluções possíveis varridas durante o processo iterativo.

Palavras-chave: otimização metaheurística, turbinas eólicas, micrositing, modelo de esteira, QPSO.

Abstract

Wind energy is increasingly participating in the energy matrix of countries as an alternative source of sustainable energy. Wind farms are the rational way to generate this type of energy and Brazil is a country that has great potential to be explored. In this work, the layout of wind farms is optimized to maximize the energy production that depends on the wind conditions of the region where the project is located, as well as the number of wind turbines available and the geographic limits for their installation. The optimization is based on a metaheuristic algorithm, QPSO, since in general the positioning of the wind towers can't be done continuously, but discretely due to the minimum recommended distances between the towers. The QPSO algorithm is tested in an evaluation named in the literature as an Ideal Case. The objective function of the problem is to achieve the increase in efficiency of generated energy resulting from the microsites to make a comparison with results obtained from the literature. For the evaluated case, the QPSO was able to find more efficient solutions than other approaches, even with greater dispersion among all possible solutions searched during the iterative process.

Keywords: metaheuristic optimization, wind turbines, micrositing, wake model, QPSO.



1. INTRODUCTION

Wind power generation is taking its place every day in the energy matrix of countries. Together with solar energy and energy obtained by biofuels, it is an important source of renewable energy. The wind is a resource that is available to virtually all countries, some of which have more favorable conditions for their exploration from wind farms (whether on land or offshore, at sea and away from the coast). An important indicative factor of wind power generation potential is the so-called Capacity Factor, which is the ratio between effective production over some time and maximum total capacity in the same period. In northeastern Brazil, this factor reached levels close to 83%, indicating the good use of wind in wind farms installed in this region (ABEEólica, 2017).

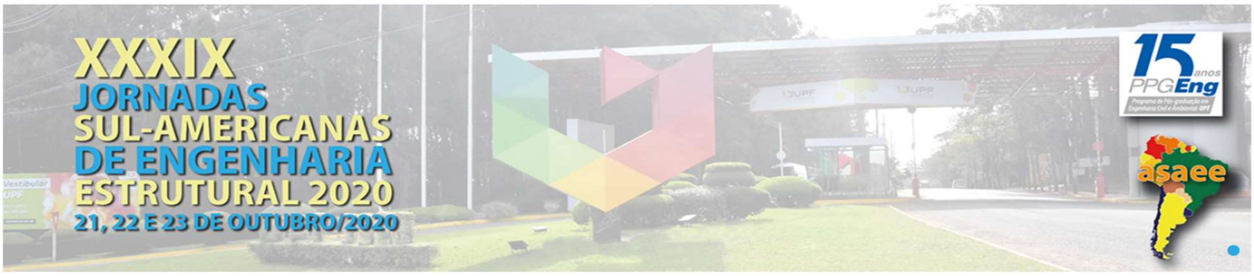
This factor is related to local climatic conditions but is also due to the performance of the installed turbines and the optimized design of the arrangement of wind turbines in the enterprise. This provision, also known as a *micrositing*, may minimize the recurrent problem of the interaction between turbulence streams generated by windward towers with the loss of efficiency of windward-positioned towers. This is a complex problem, since there is seasonality and uncertainty about the intensity of the winds and their direction, being a more desirable provision than another in terms of average energy generation.

In this sense, the main objective of this work is the development of a source code for the modeling and evaluation of wind farms layouts, in order to take into account important information such as terrain roughness, wind turbine rotor height, statistical data on annual wind direction and intensity. Using the MATLAB software (2000), a metaheuristic algorithm was proposed to optimize the arrangement of wind turbines in wind farms to increase the electricity produced and, therefore, the energy efficiency of the enterprise. Constraints on the minimum distance between wind turbines, as well as the number of wind turbines and the interaction effects between turbulence streams, were used in the optimization, being the code later validated by an example widely reported in the literature.

The paper is divided as follows: first, a brief introduction is made about the metaheuristic approach used. Then, the presentation of some concepts considered in the modeling is made, as well as the presentation of the analyzed case. Finally, the results obtained in the analyzes and the respective conclusions that can be drawn from them are presented.

2. QUANTUM BEHAVIOR PARTICLE SWARM OPTIMIZATION ALGORITHM (QPSO)

According to Sun et al. (2012), QPSO is an important evolution of the PSO metaheuristic algorithm motivated by quantum particle mechanics. Unlike PSO, it does not require velocity vectors and has fewer parameters to adjust, thus facilitating its implementation. The algorithm uses a strategy in which it benefits from its previous optimal positions and receives help from the best average position of all particles to improve the overall search capability of the solution, as a swarm particle always has a non-zero probability of being able to find itself in any position ($\boldsymbol{x}$) of the entire search space feasible, even in a position far from the best global position. This allows the possibility of increased demand in the search space. In addition, the state of each particle can be described by a wave function $\Psi(\boldsymbol{x})$ and the probability of finding the particle in a given position can be described by the probability density function $Q(\boldsymbol{x})$, defined as:



$$Q(\boldsymbol{x}) = |\Psi(\boldsymbol{x})|^2 = \frac{1}{L} e^{\frac{-2|\boldsymbol{p}-\boldsymbol{x}|}{L}}, \tag{1}$$

$$\Psi(\boldsymbol{x}) = \frac{1}{\sqrt{\boldsymbol{L}}} e^{\frac{-|\boldsymbol{p}-\boldsymbol{x}|}{\boldsymbol{L}}} \tag{2}$$

where p is a random variable expressed by Equation 4. The L parameter characterizes the "creativity" or "imagination" of the particle, described by Equation 5.

Given one of the probability density functions, using the Monte Carlo Stochastic simulation method, the particle position can be obtained by the following stochastic equation:

$$\boldsymbol{x} = \boldsymbol{p} + \frac{\boldsymbol{L}}{2} \ln(1/u) = \frac{1}{L} e^{\frac{-2|\boldsymbol{p}-\boldsymbol{x}|}{L}}, \tag{3}$$

$$\boldsymbol{p} = \varphi \boldsymbol{P} + (1-\varphi)\boldsymbol{G}, \qquad \varphi \sim U(0,1) \tag{4}$$

$$\boldsymbol{L} = 2\alpha|\boldsymbol{x} - \boldsymbol{mbest}| \tag{5}$$

where $\boldsymbol{P}$ represents the best experience (design variables of the corresponding best objective function) of the particle and $\boldsymbol{G}$ represents the average of the best experiences of all the particles of the swarm. The parameter α is known as the expansion-contraction coefficient. $\boldsymbol{mbest}$ is the average of the best position of each particle in the swarm of N_P individuals that can be expressed as follows:

$$\boldsymbol{mbest} = \frac{1}{N_P} \sum_{i=1}^{N_P} \boldsymbol{P}_i, \tag{6}$$

To sum up, the algorithm initializes with the generation of a random population of particles and lists the best particle as a function of the objective of the problem. With each new iteration, the best average position of the swarm is calculated and the current position of each particle is updated. After this process is carried out by, all particles of the problem, the value of each particle (objective function) is evaluated, and created a history of the best individual positions and the best current global position of the swarm. The process is continued until some convergence or stopping criteria are reached.

3. NUMERICAL EXPERIMENT

3.1. Problem Formulation: Wind and wake modeling

According to Custódio (2013), wind speed varies along the day, month and year. Therefore, its variation is the main characteristic to be determined, and so the existing probabilistic distribution that best describes this behavior is the Weibull distribution due to its flexibility to be able to adapt to various forms of experimental data. The Weibull probability density function for wind velocity V is expressed by the following:

$$f(V) = \frac{c}{A}\left(\frac{V}{A}\right)^{c-1} exp\left[-\left(\frac{V}{A}\right)^{c}\right], \tag{7}$$

$$A = \frac{V}{\Gamma\left(1+\left(\frac{1}{c}\right)\right)}, \tag{8}$$

where $f(V)$ is the frequency of occurrence of V, c is the form factor of the Weibull distribution and Γ is the *Gamma* function, defined by:

$$\Gamma = \int_0^{\infty} t^{z-1} e^{-t} dt \tag{9}$$

In the vast majority of cases, the conditions of speed and direction of wind incidence in wind farms are not obtained exactly at the height of the wind turbine rotor. In addition, the technological advance used in the construction of these equipment causes a trend in the increase in the height of wind turbines, which can make it impossible to capture meteorological data at the same height. Still according to Custódio (2013), in the range of height of interest for conversion of wind energy, a behavior of variation of wind speeds is observed that can be approximated by a logarithmic function. In this way, the way to predict wind speed at a certain height, more specifically at the height of the wind turbine rotor is:

$$V_0 = V \cdot \frac{ln(H/z_0)}{ln(H_{ref}/z_0)}, \tag{10}$$

where V_0 is the wind speed at the desired height, V is the wind speed at the measuring height, H is the height where you want to know the wind speed (wind turbine rotor), H_{ref} is the reference height where the wind speed was measured and z_0 is the equivalent roughness length of the terrain in question.

3.1.1. Modelling the interactions between aerodynamic wakes

According to Custódio (2013), the extraction of kinetic energy from the wind by an wind turbine causes a reduction in the speed of the air masses. In addition, turning of the turbine blades, increases the turbulence in the airflow after interaction with this structure. From this, a subsequent wind turbine that receives disturbed wind tends to extract less energy. This effect is known as an aerodynamic stream and, if not minimized, has a great impact on the total production of the wind farm.

Jensen et al. (1986), proposed a simplified model of track effect that describes the behavior of outlet air flow of wind turbines considering the characteristics of the wind turbine. This modeling can estimate wind energy after iteration accurately since it assumes that the velocity drops linearly in the direction of wind flow and that the amount of motion is conserved within the aerodynamic stream. Figure 1 indicates the main parameters considered in this modeling. The speed $V(x)$ for any position on the turbine stream is given by:

$$V(x) = U\left[1 - \frac{\left(1-\sqrt{1-C_t}\right)}{\left(1+\frac{2kx}{D}\right)^2}\right], \tag{11}$$

where $V(x)$ represents wind speed on the wind turbine of a wind turbine, U is the free wind speed of influence turbine, U_r is the wind speed right after the rotor extracts some of its kinetic energy.

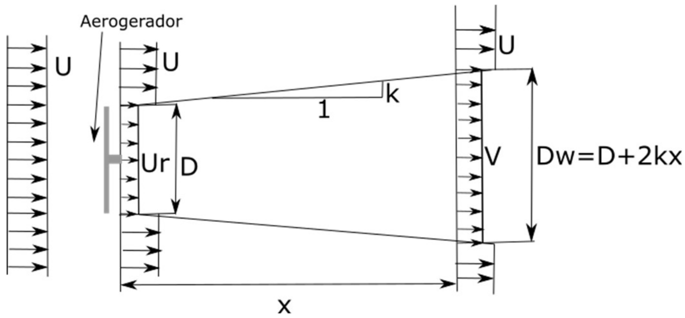


Figura 1: Schematic view of Jensen wake model.

The parameter C_t is the thrust coefficient of the turbine. Variable D is the diameter of the turbine rotor and D_W the diameter of the track at a distance x of the turbine. Factor k represents the coefficient of increase of stream, or angle of shadow opening, described by:

$$k = 0{,}5/ln(h\ /z_0) \tag{12}$$

where h is the height of the nacelle of the wind turbine (or wind turbine rotor) and z_0 is the equivalent roughness length of the soil.

3.1.2. Power production modelling

For a given wind turbine model, the power and thrust coefficient curves depend on the wind speed acting on the wind turbine. This and other machine-type data are provided by the manufacturer and are used to calculate the energy produced by the wind farm. Since in the modeling of the wake effect adopted, the layout of the arrangement of the wind turbines $(\boldsymbol{X}, \boldsymbol{Y})$ is considered, as well as a given direction of incidence of the wind θ_k and its respective velocity of incidence on the wind farm V_0, we have that the velocity of the incident wind on the wind turbine V_i is a function of all these aspects. i.e., $V_i = V_i(V_0, \theta_k, \boldsymbol{X}, \boldsymbol{Y})$. In addition, the power generated by the wind farm depends heavily on the frequency of occurrence of wind speed and its direction, represented here as the distribution of occurrence $F_{wk} = f_{oc}(V_0, \theta_k)$ and the Wind Rose. Therefore, the energy produced by the wind farm is described as:

$$P_{tot} = \sum_{i=1}^{N_{WT}} \sum_{k=1}^{N_{wd}} \sum_{w=1}^{N_{ws}} \left(V_0 \left[1 - \left(1 - \sqrt{1 - C_t(V_0)}\right) \cdot \sqrt{\sum_{j=1}^{N_{wt}} M_{ijk}} \right] \right) \cdot F_{wk}, \tag{13}$$

where N_{wd} and N_{ws} represent the number of divisions of the discretization in the Wind Rose the direction and Weibull distribution of wind speed, incidents in the wind farm, respectively.

3.2. The Ideal Case Problem and its variation

The evaluation of the proposed algorithm was based on the variation of the Ideal Case, proposed by Grady et al. (2005). This approach consists of the study of a wind farm with dimensions 50Dx50D, where D represents the diameter of the rotor of the wind turbine, where all available space for the enterprise was subdivided into 100 equal cells. Thus, a grid of cells is formed, where each location, or cell for installation has dimensions of 5Dx5D. This positioning grid, which had been used by all authors who evaluated these cases previously, acts to constrain the minimum distance between two wind turbines, that is, each turbine will be located at least at a distance of 5D from the nearest turbine. In addition, in this evaluation, the wind turbine can only be allocated in the center of each cell, which in turn further restricts the problem because it reduces the space available for wind turbine placements to a rectangular area with dimensions of 45Dx45D, given the need of 2.5D discount on each end of the initial square. In contrast to this proposal, in the present study, the position of each wind turbine, within the space available for positioning, was not restricted, that is, each wind turbine could be positioned in any location within the square of dimensions 45Dx45D, provided that the distance to the nearest wind turbine was greater than or equal to 5D.

Although in the approach that has been used by several authors there are three weather conditions (wind at 12 m/s from the north direction, wind at 12 m/s uniformly distributed in 36 directions of incidence, and wind with speeds of 8, 12, and 17 m/s uniformly distributed in 36 directions of incidence), in this study, only the first condition is evaluated due to the need to study the feasibility of the QPSO in the face of this type of optimization.

In addition, the Ideal Case, as well as its variation, evaluates the energy generated only with a type of wind turbine, which has a Tower height of 60 meters, rotor diameter of 80 meters, Thrust Coefficient of 0.88, and terrain roughness of 0.3 meters. The power curve of the wind turbine is displayed in Fig. 2.

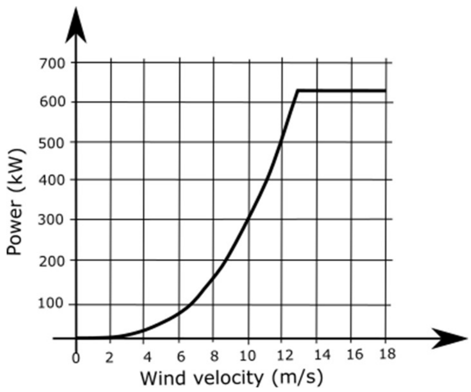


Figure 2: Wind turbine power curve.

3.2.1. Numerical experiments

To evaluate the QPSO algorithm given the optimization of the layout of a wind farm, one case where wind speed and incidence direction are constant was evaluated. After all the iterations required to stop the algorithm, it returned the value of the energy efficiency (objective function) of the best configuration. The new efficiency was compared with values in the literature and the percentage increase was evaluated for each situation.

The evaluation of this case was carried out according to the proposal of Feng and Shen (2015) in which a layout is randomly generated for the first evaluation of the algorithm and then, after the end of all iterations, it processes the relative percentage comparison between the energy efficiency found by the new micrositings and the better energy efficiency found by Grady et al. (2005). Table 1 below shows the comparison between the best, the average, and the worst of the increases related to the efficiency of Grady et al. (2005) found by the QPSO in the face of the additions found by the RS-new of Feng and Shen (2015), for the wind conditions with constant speed and direction of incidence.

Table 1: Relative increase in efficiency compared to Grady et al. (2005).

Algorithm	Maximum (%)	Average (%)	Minimum (%)	Standard Deviation
RS-new (Feng and Shen (2015))	6,35	5,92	5,48	0,33
QPSO	8,55	7,36	5,17	0,59

In terms of average values, the QPSO presents a value considerably higher than that obtained by Feng and Shen (2015), but the variability of the efficiency increases achieved by the QPSO characterizes it as slightly less robust compared to RS-new. Nevertheless, it was possible to verify that the algorithm, as well as the metaheuristic approach, was able to evaluate the micrositing of a wind farm with a high number of wind turbines delivering better results than those reported in the literature.

Figure 3 presents a comparison between the most efficient micrositing obtained by the QPSO and the most efficient ones obtained by RS-new, Feng and Shen (2015), and GA, by Grady et al. (2005).

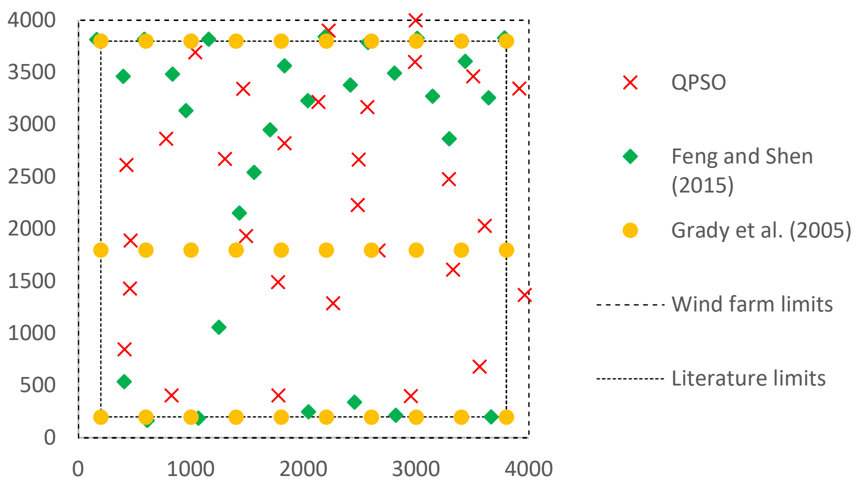
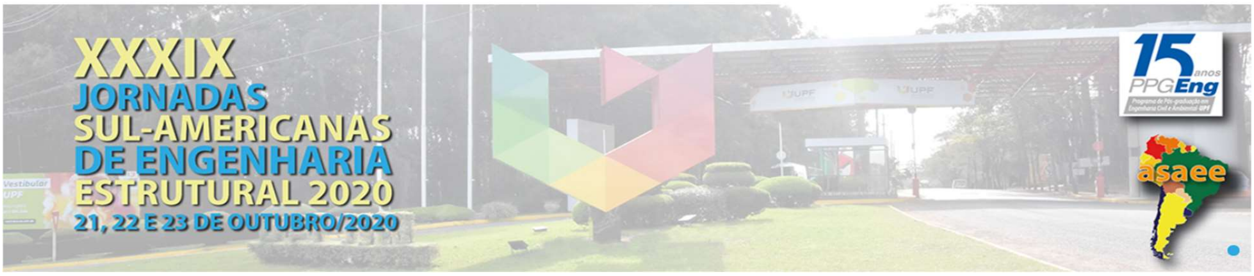


Figure 2: Comparison of micrositings obtained by different optimization methods for ideal case variation.

It can then be seen that there was a slightly similarity between the configurations proposed by the QPSO and the RS-new with regard to the position of the vast majority of towers, unlike the GA proposal in which the towers are simply lined up.

4. CONCLUSIONS

This work was proposed to optimize the micrositing of wind farms using a metaheuristic approach via the QPSO algorithm. Behaviors such as the interaction of aerodynamic tracks



resulting from disturbances in wind flow, the distribution of wind speed probabilities and their directions, power curves and thrust coefficient of wind turbines as well as distance limitations between wind turbines and geographical limits of the wind farm area were taken into account in this work.

The example of the variation of the Ideal Case, proposed by Grady et al. (2005) and composed of 30 wind turbines, was used to verify the codes developed in MATLAB (2000) and here implemented. In this case, the proposed algorithm was able to find better results of energy efficiency compared to values indicated in the literature, proving the efficiency of this metaheuristic approach in solving this type of problem. The robustness of the algorithm was proven from multiple independent rounds, obtaining a relatively small coefficient of variation, concerning the maximum values found for efficiency, but which was still higher than cases reported in the literature.

Despite this, improvements in the interaction model of aerodynamic wind turbines, in addition to the parallelization of the algorithm, a greater discretization of anemometric data or also the replication of this methodology in a wind farm located in Brazil are suggestions for future work. Such proposals can be easily implemented, which, in turn, allows the analysis of more complex cases, both with a greater number of wind turbines, as well as a more complex discretization of wind incidence directions and terrain area limits for park installation.

Acknowledgment

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