

OFFSHORE WIND FARM OPTIMIZATION VIA COMPUTATIONAL INTELLIGENCE

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RESUMO

O presente trabalho tem como objetivo comparar os desempenhos de duas técnicas recentes de inteligência computacional, *Grey Wolf Optimizer* (GWO) e o *Sine Cosine Algorithm* (SCA), na resolução do problema de otimização de um parque eólico offshore, contemplando o layout das turbinas. Para tanto, foi considerada uma região do litoral do nordeste, foram utilizados dados de vento da região, curvas de geradores em estudo e dados de cabos de um fabricante a fim de otimizar um parque de 500 MW de capacidade instalada. Ambos os métodos tiveram performances parecidas e a melhor solução foi obtida através do SCA.

PALAVRAS CHAVE. Otimização do Layout, Wake Effect, Metaheurísticas, Algoritmo Seno Cosseno, Otimização dos Lobos Cinzentos.

Tópico: EN - PO na área de energia / MH - Metaheurísticas

ABSTRACT

The present work aims at comparing the performance of two recent computational intelligence techniques, *Grey Wolf Optimizer* (GWO) and the *Sine Cosine Algorithm* (SCA), in solving the offshore wind farm layout optimization problem. To do so, the wind data from a coastal area in the northeastern region was considered, as well as the power curves of a commercial wind turbine, and cable data from a manufacturer to optimize a 500 MW farm of installed capacity. The methods had similar performances and the best solution was obtained by the SCA algorithm.

KEYWORDS. Layout Optimization, Wake Effect, Metaheuristics, Sine Cosine Algorithm, Grey Wolf Optimization.

Paper topics: EN - OR in energy area / MH - Metaheuristics

1. Introduction

1.1 Wind Energy Overview in Brazil and Worldwide

The world energy matrix has been witnessing a continuous increase in the number of ventures and installed capacity of wind farm power plants. According to the Global Wind Energy Council (GWEC) report, 51.3 GW of installed capacity were added in 2018. Besides that, an increase of 300 GW is expected within the next 5 years, with a considerable participation of offshore ventures [GWEC, 2019].

Figure 1 depicts the growth in the installed wind power capacity, and shows the forecast for the next 5 years.

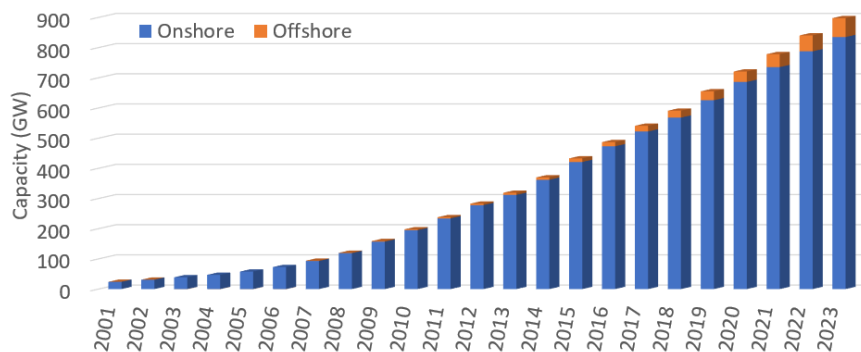


Figure 1 – Installed Capacity Growth (Source: GWEC).

Thus, it is possible to verify that the offshore ventures are gaining increasing visibility in the world. These ventures present some advantages, such as a better use of wind and greater generation potential, despite requiring greater investments in construction technologies.

According to the Decennial Expansion Planning 2027, there is a forecasted expansion of wind power in Brazil. Figure 2 depicts the annual installed capacity forecast data by 2027.

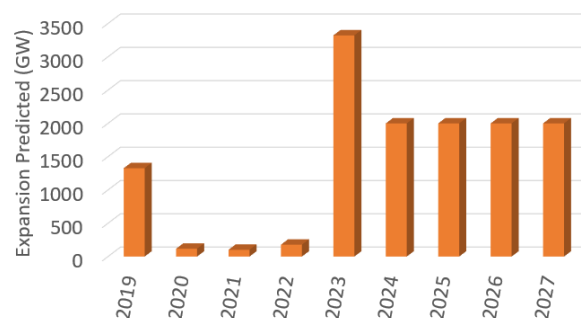


Figure 2 – Wind power annual installed capacity forecast data. (Source: PDE 2027)

Besides that, according to the Brazilian wind potential atlas – CEPEL – one of the regions with the greatest offshore wind potential is the northeastern region, which has higher wind speeds.

This way, this work presents a study for a region in the coastal area in the State of Ceará, in which real wind speed and direction data will be considered in the simulations.

1.2. Related Work

Several optimization algorithms are being used to solve the wind turbine layout optimization problem, both in onshore and offshore wind farms. The application of intelligent techniques by evolutionary computation and swarms intelligence are widely used due to the

combinatorial nature of the decision process, which involves continuous and discrete variables. Genetic Algorithms (GA) and variations are used in [Changshui et al., 2011], [Wu et al., 2014], [Duan et al., 2014], [Shakoor et al., 2014] and [Gao et al., 2015], meanwhile in [González et al., 2010], [Kusiak and Song, 2010] and [Jiang et al., 2013] the authors choose to use Evolutive Algorithms (EA). The technique named Artificial Immune System (AIS) is used in [Gomes et al., 2017] and [Panoeiro et al., 2018a]. In [Pookpunt et al., 2012], [Hou et al., 2015] and [Yang et al., 2016], the authors propose the use of Particle Swarm Optimization (PSO) methods, and in [Panoeiro et al., 2018b] the Bat Algorithm is used.

1.3. Work Contributions

Following this line of research, the present work proposes to compare two recent techniques, Grey Wolf Optimizer (GWO) and Sine Cosine Algorithm (SCA), applied to the offshore wind farm layout optimization problem. These techniques are able to perform both global and local search efficiently, being widely used in the resolution of several optimization problems in the last few years.

Besides that, a study case will be presented, since the used data refer to a coastal region in the north of the State of Ceará.

2. Problem Data and Formulation

2.1. Wind Data

A region in the north of the State of Ceará was selected for the installation of a 500 MW wind farm. The wind data used in this work was obtained through the Vortex platform, in which the wind speed and direction data were obtained for the geographic coordinate point (2.5°S, -40°W). The obtained data have hourly discretization in an annual basis for the year of 2012. The wind velocity values and wind rose are presented on Figure 3.

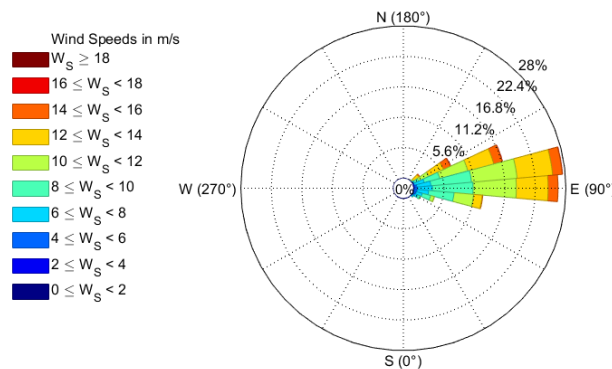


Figura 3 - Distribuição de velocidade e direção de ventos

This work will consider a constant wind speed of 10.4653 m/s, which is the mean wind speed for this point in 2012. In terms of wind direction, the authors will consider only the 3 directions with the greater probability of occurrence. Table 1 depicts the directions and their respective normalized probabilities.

Table 1 – Wind directions and probabilities

Direction	Probability
90°	37.38 %

100°	38.69 %
110°	23,94 %

2.2. Wake Effect

The interaction between the wind and the wind turbine causes the wind kinetic energy to be harnessed and converted into electric energy. After interacting with the turbine, the wind continues its course, but gets weakened due to energy loss. This interaction was mathematically modeled through the mass flow conservation by [Jensen, 1983]. Through this model, it is possible to determine the wind speed at any point located downstream of a wind turbine.

According to the model proposed by Jensen, the interaction between the wind and the turbine generates a conic region located downstream, in which the velocity u_i that impinges on the turbine i suffers a reduction, as shown in Figure 4.

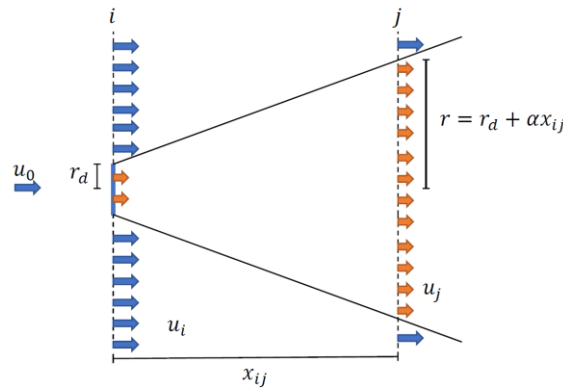


Figure 4 - Wake Effect.

Considering a turbine j located downstream of a turbine i in the conic region, the wind speed that impinges on it is calculated by Equation (1).

$$u_j = u_0 \left[1 - \left(\frac{2a}{1 + \alpha \left(\frac{x_{ij}}{r_i} \right)^2} \right) \right] \quad (1)$$

In Equation (1), x_{ij} is the distance between turbines i and j in the direction of the wind incidence. r_j is the effective radius of the rotor located downstream related to the upstream rotor radius r_i , according to Equation (2). a is a constant which is associated with the impulse coefficient C_t according to Equation (3). α is a constant associated with the soil roughness z and the height of the wind turbine z_0 , and this relation is depicted by Equation (4).

$$r_i = r_j \sqrt{\frac{1-a}{1-2a}} \quad (2)$$

$$C_T = 4a(1-a) \quad (3)$$

$$\alpha = \frac{0,5}{\ln\left(\frac{z}{z_0}\right)} \quad (4)$$

In the situations in which there are n_u upstream wind turbines impacting the wind velocity that affects downstream turbines, the wind speed loss percentage caused by each wind turbine must

be computed using Equation (1). Then, an average percentage value is calculated for velocity losses W_{med} before reaching each wind turbine, as shown in Equation (5).

$$W_{med} = \sqrt{\sum_{i=N}^{n_u} \left(1 - \frac{u_j}{u_0}\right)^2} \quad (5)$$

The resulting velocity at wind turbine j is then determined by Equation (6).

$$u_j = u_0(1 - W_{med}) \quad (6)$$

2.3. Wind Turbine Data

The necessary data to solve the problem are presented on Table 2.

Table 2 – Simulation Parameters.

Parameter	Value
Rotor Diameter [m]	180
Rated Power [MW]	10
C_T	0,88
Hub Height (z) [m]	120
Soil roughness (z_0)	0,3

The wind turbine power curve was obtained through an approximation from the curve given in the manual of the model DTU10MW [Bak et al., 2013]. The expression of the power generated as a function of the incident velocity v in m/s is shown in Equation (7) and the graph of the power curve is depicted in Figure 5.

$$P_{kW}(u) = \begin{cases} 0, & \text{if } u < 4 \\ 7,056u^3 & 4 \leq u \leq 11,23 \\ 10000 & 11,23 \leq u \leq 25 \\ 0, & \text{if } u > 25 \end{cases} \quad (7)$$

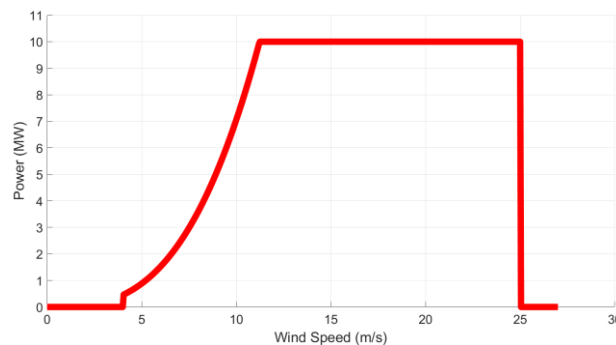


Figure 5 – Extracted power as a function of wind speed incidence.

2.4 Impacts of the Incidence Angle on the Extracted Power

Jensen's analytical model takes into account that the wind turbine will be positioned in a way that it is reached by the wind perpendicularly to the plane defined by the rotation of the blades. However, due to the extension of the conical area, the wind incidence angle can impact the power extracted from the turbines.

To exemplify this situation, a literature wind farm and its data was considered [Pookpant, 2013]. The incidence angle θ was varied from -90° and 90° in a farm composed of 30 wind turbines and the the extracted power of the array was obtained with respect to its capacity. The adopted wind farm is shown in Figure 6a. The graph obtained from the variation of θ is depicted in Figure 6b.

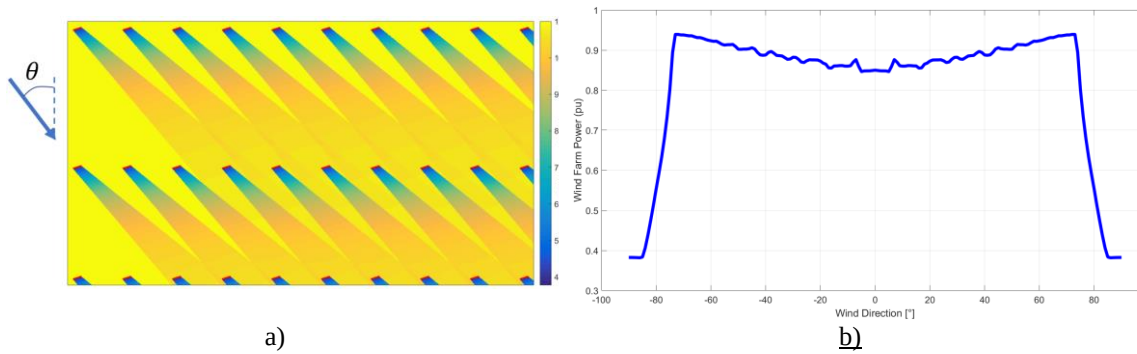


Figure 6 – Wind direction influence in extracted power.

It is observed that the wind direction impacts the extracted power output, and, therefore, should be considered in the resolution of the wind turbine positioning problem.

2.5. Problem Formulation

This work aims at determining the optimal layout of 50 turbines in an offshore wind farm to obtain the maximum power output from the wind turbines. The wind farm region was divided in 100 bits and the optimization variable $\mathbf{x}$ is a vector of 100 positions in which each can either assume the value 0 (meaning that there is not a turbine in this bit) or 1 (meaning there is a turbine in this bit). Thus, each vector corresponds to a possible layout.

This way, Equation (8) represents the objective function, in a simplified way, in which the i -th turbine wind speed u_i is obtained through the model of the Wake Effect phenomena, previously explained, θ_{dir} depicts the incidence angles for the dir directions with probabilidade P_{dir} and P_{kw} is the power extracted from the wind speed u_i as shown in Equation (7).

$$\text{Max} \sum_{dir=1}^3 \left(P_{dir} \cdot \sum_{i=1}^{50} P_{kw}(u_i(\mathbf{x}, \theta_{dir})) \right) \quad (8)$$

3. Computational Intelligence – Investigated Methodologies

The stochastic optimization methods named computational intelligence are the methods commonly applied to the optimal wind turbine layout problem. In different study areas, applications are found using these techniques due to the implementation simplicity, flexibility in adapting to the problem and to avoid derivation mechanisms. In general, these techniques are quite used in nonlinear problems, with nonconvex solution region (with plenty local maxima and minima) and large dimensions, as in the case of obtaining the optimal layout of a wind farm.

In the specialized literature, different classifications regarding computational intelligence are found, such as: (a) algorithm's inspiration (biological, physical, chemical, among others) and (b) the number of solutions involved in the optimization problem (individuals or populations) [Mirjalili, 2016]. The techniques based on populations normally utilize a set of initial solutions, that is improved with the course of iterations (search process). In the solution searching process, each technique has its own characteristics/operators that allow a search through all the region (global search) and around promising regions (local search) [Mirjalili, 2014].

In the present work, as previously mentioned, the authors chose to investigate two recent population-based techniques, aiming at evaluating which technique is the most efficient one to solve the wind farm layout optimization problem. To do so, the authors implemented the Grey Wolf Optimizer (GWO) and the Sine Cosine Algorithm (SCA), developed by [Mirjalili et al., 2014] and [Mirjalili et al., 2016], respectively.

3.1 Grey Wolf Optimizer – GWO

The GWO algorithm (Mirjalili et al., 2014) is based on the social hierarchy and hunting behavior of grey wolves. The grey wolves' hierarchy is divided in alphas, betas, deltas and omegas, respectively in order of dominance. The alpha wolf, also named dominant wolf, is the main responsible for making the decisions, e.g., time to hunt, places to sleep and wake up times. The beta wolf is the alpha's right hand and helps in the decision-making process. The delta wolves belong to the categories of scouts, sentinels, elders, hunters and caretakers. At last, the omega wolves compose the lowest level of the hierarchy and play the role of scapegoats. The wolves hunting strategy is divided into three steps: (i) tracking, chasing and approaching the prey; (ii) chasing and encircling until stationary situation; (iii) attacking the prey.

Algorithm 1 – Pseudocode: GWO

1 : Initializing wolves population: X_i ($i = 1, 2, 3 \dots N_{Wolves}$)
2 : Wolves evaluation: $OBJ(X_i)$
3 : Hierarchy definition: ($X_\alpha, X_\beta \in X_\delta$)
4 : While stopping criteria not met, do:
5 : Update searching parameter: a^t
6 : Loop 1: N_{Wolves}
7 : $\vec{A} = a^t \cdot \vec{r}_1 - a^t, \quad \vec{r}_1 \in [0, 1]$
8 : $\vec{C} = 2 \cdot \vec{r}_2, \quad \vec{r}_2 \in [0, 1]$
9 : $\vec{D}_\alpha = \vec{C}_1 \cdot \vec{X}_\alpha^t - \vec{X}_i^t , \vec{D}_\beta = \vec{C}_2 \cdot \vec{X}_\beta^t - \vec{X}_i^t , \vec{D}_\delta = \vec{C}_3 \cdot \vec{X}_\delta^t - \vec{X}_i^t $
10 : $\vec{X}_1 = \vec{X}_\alpha^t - \vec{A}_1 \cdot \vec{D}_\alpha, \vec{X}_2 = \vec{X}_\beta^t - \vec{A}_1 \cdot \vec{D}_\beta, \vec{X}_3 = \vec{X}_\delta^t - \vec{A}_1 \cdot \vec{D}_\delta$
11 : $\vec{X}_i^{t+1} = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3}$
12 : Update wolves hierarchy: $X_\alpha, X_\beta \in X_\delta$
13 : End Loop
14 : End While

In the GWO algorithm, the size of the wolves population is defined (N_{wolves}), whose positions represent the number of solutions investigates within the solution region (X_i), which are randomly initialized. The solutions are evaluated through the evaluation of the objective function and the hierarchy of the wolf pack is defined, where the three best solutions of the set give rise to the alpha (X_α), beta (X_β) and delta (X_δ) wolves, respectively in order of superiority.

After the initialization process, the iterative process of the algorithm starts, i.e., the hunting step that will update the position of the wolves of the entire pack. To perform such update, the search coefficients $\vec{A}$ and $\vec{C}$ are calculated as depicted in the lines 7 and 8 of the GWO pseudocode. These coefficients enable the global or local search during the wolves position update step. For $A < 1$, the wolves are forced to attack the prey (converge to the best solution) and for $A > 1$ the wolves search for better preys in the search space (diverge from the best solution). In the case of the vector C, if $C < 1$ or $C > 1$ attenuates or increases the magnitude of the best solution in the searching mechanism. The component a^t decreases from 2 to 0 over the course of the t iterations.

Then, the wolves positions are updated. Lines 9 and 10 represent the behavior of the wolves encircling the prey during the hunting process, whose location is identified by the alpha, beta and delta wolves. Therefore, the estimate position ($\vec{X}_i^{t+1}$), of the wolf is defined on line 12 by the mean

displacement with respect to the positions of the dominant wolves. At last, the wolves hierarchy is updated.

3.2 Sine Cosine Algorithm – SCA

The optimization tool SCA (Mirjalili, 2016) is considered a population-based optimization technique based on the mathematical functions sine and cosine, in which the local and global search components are made according to random adaptive variables integrated to the algorithm.

Just like the algorithm described on Section 3.1, in the SCA algorithm the total number of solutions is defined. These solutions are randomly dispersed in the solution region and evaluated by the objective function. Then, the algorithm search process begins, whose exploration for the optimal solution is performed by the approximation between the solution X_i^t (current position) and the best solution (P^*). The solutions update (X_i^{t+1}), are represented on line 8, whose random value between $[0,1]$ of the parameter r_4 determines the choice of the sine or cosine component.

Algorithm 2 – Pseudocode: SCA

1 : Solution initialization: X_i ($i = 1, 2, 3 \dots N_{sol}$)

2 : Solution evaluation: $OBJ(X_i)$

4 : Determine best solution (P^*)

5 : **While** stopping criteria not met, do:

6 : Update searching parameter: $r_1^t = a - t \frac{a}{T_{max}}$

7 : Loop 1: N_{sol}

8 :
$$X_i^{t+1} = \begin{cases} X_i^t + r_1^t \cdot \sin(r_2) \cdot |r_3 \cdot P^* - X_i^t|, & r_4 < 0,5 \\ X_i^t + r_1^t \cdot \cos(r_2) \cdot |r_3 \cdot P^* - X_i^t|, & r_4 > 0,5 \end{cases}, \quad \begin{matrix} r_2 \in [0, 360^\circ], r_3 \in [0, 1], \\ r_4 \in [0, 1] \end{matrix}$$

9 : Update best solution (P^*)

10 : End Loop

11 : End While

The parameter r_1 is a function of the maximum number of iterations (T_{max}), the current iteration (t) and an exploration constant (a). Therefore, this parameter decreases over the course of the process, leading to global search at the beginning and local search at the end of the process. When $r_1 < 1$, it is estimated that the position can be in the region between the current solution (X_i^t) and the best solution (P^*) or outside this region if $r_1 > 1$. As for the parameter r_2 , it is related to the extension of the step towards or outwards the best solution. $r_3 < 1$ or $r_3 > 1$ attenuates or increases the magnitude of the best solution, respectively. At last, the best solution position is updated (P^*).

4. Simulations and Study Cases

In [Panoeiro, 2018a] and [Panoeiro, 2018b] new methodologies were proposed to solve this problem and the results were compared with [Pookpant, 2013]. The results present a new configuration of the wind farm, considering different wind speed and directions data.

As previously mentioned, a region in the north of the State of Ceará was selected for the installation of a 500 MW of installed capacity wind farm, composed by 50 wind turbines. The region was divided in 100 bits, in which the distance between the bits is equal to 900 m, equivalent to 5DR [Pookpant and Ongsakul, 2013].

The optimization process will be binary, in which the variable will be a vector of 100 positions. The stopping criteria for both algorithms is the number of iterations. The simulations were made with the following setups:

- Populations of 100, 500 and 1000 individuals;

- Maximum number of iterations: 100 and 300;
- Incidence angles: 0° and multiple directions (90°, 100° and 110°) with its respective probabilities;

For each setup, a total of 10 simulations were made and the best solutions obtained. The evaluation of each method was made considering the mean and standard deviation of the obtained results. Table 3 depicts the results obtained through the simulation for North-South case, at which the incidence angle is of 0°. Table 4 depicts the results obtained for multiple wind directions.

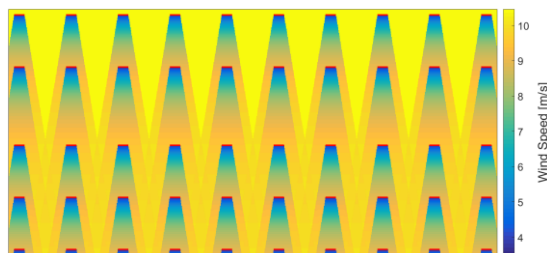
Table 3 - Results of North-South case.

Number of Iterations	Number of Solutions	SCA			GWO		
		Mean [MW]	Standard Deviation [MW]	Best OBF [MW]	Mean [MW]	Standard Deviation [MW]	Best OBF [MW]
100	100	289,798	1,295	291,535	291,056	1,515	292,913
	500	292,417	0,826	294,002	291,866	1,089	293,97
	1000	293,03	0,881	294,034	292,025	0,822	292,974
300	100	291,512	1,228	293,182	291,344	1,489	293,402
	500	292,816	0,724	294,002	292,622	0,8	293,516
	1000	293,127	0,781	294,034	292,299	1,503	294,034

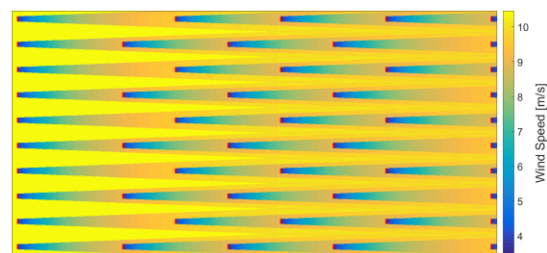
Table 4 - Results of Multiple Directions case.

Number of Iterations	Number of Solutions	SCA			GWO		
		Mean [MW]	Standard Deviation [MW]	Best OBF [MW]	Mean [MW]	Standard Deviation [MW]	Best OBF [MW]
100	100	327,592	1,489	329,664	327,469	1,425	329,11
	500	329,571	0,841	330,552	329,483	1,017	331,093
	1000	329,344	1,282	331,203	329,397	0,632	330,11
300	100	329,091	0,768	330,271	329	0,800	330,213
	500	330,113	0,989	331,243	330,1	0,906	331,249
	1000	329,826	0,897	331,874	329,783	0,759	331,085

Figure 7a) shows the layout obtained for the North-South case for the best objective function (OBF). Figures 7b), c) and d) show the wind speed profile of the farm for the angles of 90°, 100° and 110°.



a) North - South – PT = 293,91 MW



b)90° - PT = 292,98 MW

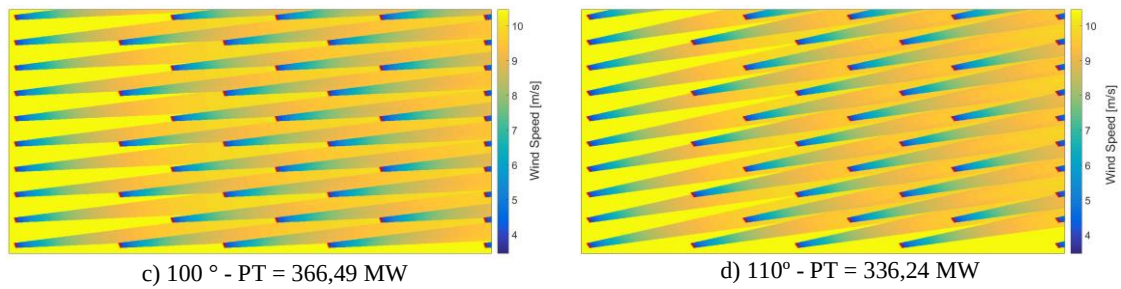


Figure 7 – a) Optimal Layout considering North-South direction. b) Wind speed profile for an angle of 90°. c) Wind speed profile for an angle of 100°. d) Wind speed profile for an angle of 110°.

Table 5 – Mean computational time for each case, in seconds.

Number of Iterations	Number of Solutions	North-South		Multiple Directions	
		SCA	GWO	SCA	GWO
100	100	24	23	51	52
	500	83	84	236	242
	1000	174	177	483	484
300	100	52	52	135	138
	500	350	357	837	862
	1000	641	660	1347	1320

6. Analysis and Conclusions

In this work, two optimization algorithms were implemented to determine the optimal layout of wind turbines in an offshore wind farm in the Northeastern region of Brazil. Analyzing the performance of both algorithms, it was verified that an increase in the number of iterations leads to smaller deviations on the best obtained solution. This meets the expectations, since an increase in the number of iterations enables the algorithms to search for better solutions for longer. Also, it was verified that an increase in the population led, in most cases, to better results, which also meets the expectations.

For the North-South case, it was verified that the best solution was obtained with 100 and 300 iterations with an OBF of 229.034 MW, equivalent to a 45.8% capacity factor. It can be seen that 19.1% of the installed capacity is not extracted due to the wind velocity, which is smaller than the rated velocity, and that 35.1% is not extracted due to the Wake Effect.

This impact on the capacity factor caused by the Wake Effect highlights the importance of its consideration on the determination of the turbines positioning at the wind farm.

By analyzing the wind's incidence direction, it was verified that wakes of neighboring turbines, due to its conical shape should also be considered to avoid Wake Effect losses. It was verified that the maximum power extraction of the farm happened for an angle of 100°. In this case, the power output was of 366,49 MW representing a capacity factor of 73,3% in which 19,1% is related to the wind speed and 7,6 % is associated with the Wake Effect.

This work considered the 3 most-likely wind directions scenario to occur, and the mean wind speed for the region for the year of 2012. It is important to highlight that the direction and velocity vary over time and, therefore, many scenarios of both factors must be considered for a broader planning of the wind farm.

7. Future works

Another factor that influences in the output extracted power from the farm is related to the losses in the collector system, which is associated to the distance between the wind turbines and the substation. Thus, the effect of these losses in the output power extracted will be determined in future works. Besides that, the binary and discrete modeling for this problem can be a limiting factor for the problem, by reducing the total power extracted from the wind farm. Therefore, a continuous modeling approach can also be highlighted as future work.

8. Acknowledgements

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