Offshore Wind Farm Layout Optimization Regarding Wake Effects and Electrical Losses

Luís Amaral, Under Supervision of Prof. Rui Castro

***Abstract*—In the last years, a great development of the wind energy market has been witnessed increasing the number of offshore wind parks. Since the implicated costs are higher, it is extremely important to ensure that the energy production is maximum, so that the costs per energy unit may decrease.**

Thus, the turbines should be strategically positioned to extract as much energy as possible from the wind. In order to accomplish that, wake effect losses, as well as internal grid electrical losses, should be considered. There are two techniques that may have better CPU time performance than the deterministic algorithm in what concerns the optimization of the problem mentioned above. They are the Genetic Algorithm and the Particle Swarm Optimization, which will be approached in this thesis.

Turbines should be distributed according to a certain logic by a grid of cells; each of these is divided in multiple sub-cells. After each turbine is assigned to one cell, it should be placed in the centre of one sub-cell. In this way, the goal is to allow the position of the wind turbine not to be limited just to the centre of its own cell.

This MSc thesis deals with the wind park layout optimization problem by developing a method to position the turbines inside a wind park that maximizes the annual energy production through losses the minimization. The results proved that the meta-heuristic method is CPU time efficient in providing the maximum annual year production as compared to the traditional deterministic approach.

***Index Terms*—Offshore Wind Energy, Electrical Losses, Wake Effect, Genetic Algorithm, Particle Swarm Optimization.**

I. Introduction

OVER the past decade, wind energy was the fastest growing of renewable energy [1], reaching the 128 GW of installed capacity only in Europe [2]. According to EWEA [3], in 2030 the installed capacity will increase and reach 320 GW. Until 2006, offshore wind energy had a small parcel on the total wind energy installed but, as depicted in Fig. 1, that parcel has been growing since than and it is expected to continue to grow once the best locations onshore are already occupied.

Indeed, going offshore can tackle some disadvantages of the onshore wind energy development, as: the availability of large continuous areas, suitable for major projects; the elimination of visual impact and noise issues, allowing the utilization of bigger turbines [4]; stronger and less turbulent wind, increasing the energy produced [5]; higher air density resulting in higher wind power output.

In spite of considerable disadvantages related to the development of wind energy offshore (mainly the increase of investment costs and low accessibility), these can be softened if the annual energy production (AEP) is highly enough to

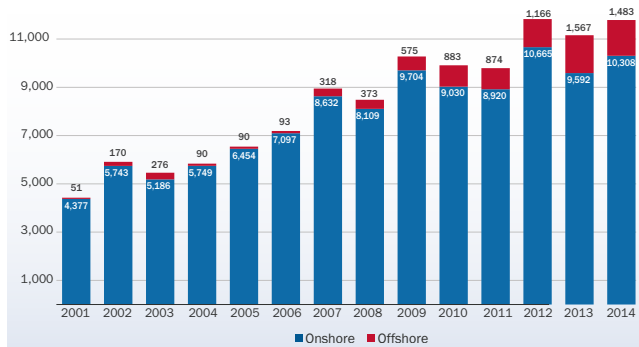

Fig. 1. Annual onshore and offshore installations [MW]. From [2].

reduce the overall levelized cost of energy (LCOE). To achieve this purpose, new techniques should be introduced. Wind Farm Layout Optimization Problem (WFLOP) is an example of such research, since by optimizing the turbines disposal, losses are reduced (both aerodynamic and electrical) and the energy production increased, thus reducing the LCOE.

The WFLOP is a multidisciplinary problem, including several design variables which increase with the number of wind turbines. In addition, various restrictions should be considered if the purpose of setting the problem on a more realistic basis is desired. Among others they include, the minimization of both the wake effect and electrical losses in the internal collection system. This is not trivial, as the former decrease with the separation distance of the wind turbines while the latter increase with the separation distance. Hereupon, understanding the aerodynamic aspects involved in the wake losses of a wind farm is a very important objective, but investigating the electrical internal infrastructure of a wind farm is of equal importance.

II. Wake Effect

Wind turbines extract energy from the wind, therefore the downstream wind (the one that leaves the turbine) must have less energy content than the upstream [6]. To the affected wind it is called wake.

The aerodynamic interaction between turbines has been the subject of many researches. Nowadays, there are many available models to study the wake diameter and the wind speed variations over the distance (e.g. Jensen Model [7], Frandsen Model [8] and EWTS-ii Model [9]). Some of these models are simpler than the others and, consequently, with lower precision, but they present faster computation times. In this report, the Jensen Model proposed by Mosetti et al. [10]

and applied in other studies (e.g. [11] and [12]) is considered once it proven to be computationally efficient and has a satisfactory degree of precision.

A. Wake Model

The model consists of a cone with a linear expansion of the wake diameter and a linear decay of the velocity deficit inside the wake. The wake radius, r_1, is given by equations (1) and (2):

$$r_1 = \alpha x + r_r \tag{1}$$

$$\alpha = \frac{1}{2\log\left(\frac{z}{z_0}\right)} \tag{2}$$

where x is the downstream distance, r_r is the upstream turbine rotor radius, z is the hub height and z_0 is the surface roughness length. The roughness length value for water surface is usually 0.0002 [13]. The wake model is represented in Fig. 2.

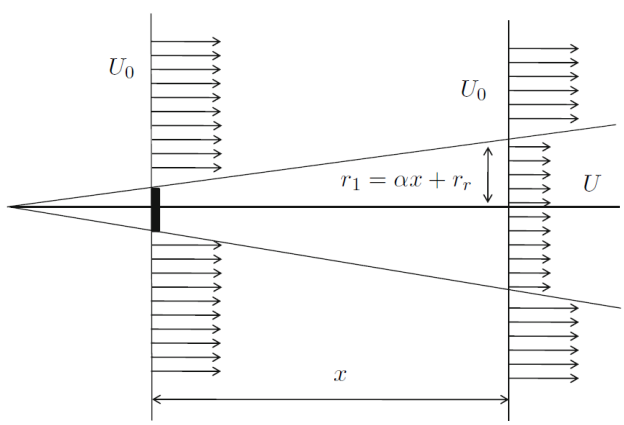

Fig. 2. Schematic representation of wake wake model.

The velocity deficit inside a single wake, vd, at distance x is given by the following equations:

$$vd = \frac{2a}{1+\alpha\left(\frac{x}{r_1}\right)} \tag{3}$$

$$a = \frac{1-\sqrt{1-C_T}}{2} \tag{4}$$

where C_T is the thrust coefficient determined by the turbine manufacturer. In this report, C_T is always 0.88. The wake radius can be related to the rotor radius as function of the axial induction factor, a, and has the following expression:

$$r_1 = r_r\sqrt{\frac{1-a}{1-2a}} \tag{5}$$

The wind velocity behind a turbine, i.e. a single wake velocity, U, is given by:

$$U = U_0\left[1 - vd\right] \tag{6}$$

where U_0 is the upstream wind speed.

B. Multiple Wake Effect

In a wind farm where there are many turbines installed it is most likely that wakes can intersect and affect turbines downwind at the same time [1]. Let turbine j be the turbine that it's being studied and turbine i an upwind random turbine. Then, one can write:

$$v_{def}(j) = \sqrt{\sum_{i\in upwind}(vd_{ij})^2} \tag{7}$$

where vd_{ij} is the same deficit from (3) but between turbines i and j distanced from x_{ij} distance. Now, (3) can be written as:

$$vd_{ij} = \frac{2a}{1+\alpha\left(\frac{x_{ij}}{r_1(x_{ij})}\right)} \tag{8}$$

where $r_1(x_{ij})$ is the wake radius from (1) but now it depends on x_{ij}.

A turbine that is aerodynamically affected by other is said to be under the shadow area of an upstream turbine and that shadow may not fill the entire downstream swept area. Thus, the concept of shadowing ratio, A_{ratio}, is introduced:

$$A_{ratio} = \frac{A_{shadow}}{A_{turb}},\ A_{ratio} \in [0,1] \tag{9}$$

where, A_{shadow}, is the downstream shadowed area and A_{turb} is the downstream swept area. The term A_{ratio}=0 means that there is no wake effect and A_{ratio}=1 means that the wake is total.

Gathering equations (7)-(9) together, we come to the total velocity deficit on a downstream turbine j, $v_{def}(j)$ [14]:

$$v_{def}(j) = \sqrt{\sum_{i\in upwind}\left[vd_{ij}.A_{ratio}(i,j)\right]^2} \tag{10}$$

And the finally, the total wind speed that passes through a wind turbine j is:

$$U(j) = U_0\left[1 - v_{def}(j)\right] \tag{11}$$

III. Electrical System

Wind parks electrical connections are responsible for collecting the energy from wind turbine generators (WTGs) and transport it to shore where it can be used. As any electrical system, it has losses that have a significant impact on the energy delivered to the main grid.

In this report, two distinct electrical systems are considered: the internal grid network that is responsible for collecting the power from WTGs and deliver it to the substation; the transporting system that transmits the energy from the substation to shore. The latter isn't approached once it doesn't influences directly the wind farm layout.

A. Turbine Power

Turbines are designed to work within a certain range of wind speeds, known as cut-in, u_0, and cut-out , $u_{\max}$, wind speeds. But, on one hand, for wind velocities lower than u_0 the operation costs are too high for what the turbine yields, as so the WTG is disconnected. On the other hand, when speeds are higher than $u_{\max}$, the generator is shut down so as to avoid damaging the equipment. The power curve, i.e. the electrical power output as a function of the wind speed, is represented in Fig. 3. (P_R and U_N are, the rated electrical power output and the rated wind speed, respectively).

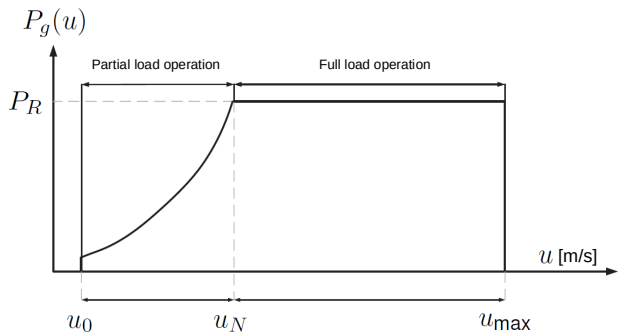

Fig. 3. Ideal power curve of a typical WTG.

The power curve can be described as a sigmoid function [13]:

$$P_g(u) = \begin{cases} 0 & , \quad u < u_0 \\ \frac{P_R}{1+e^{-\frac{u-c_1}{c_2}}} & , \quad u_0 \leq u < u_N \\ P_R & , \quad u_N \leq u < u_{\max} \\ 0 & , \quad u > u_{\max} \end{cases} \tag{12}$$

where P_R is the WTG rated power and $c_{1,2}$ are constants that need to be determined, in order that the sigmoid function fits better when compared with real samples. In this report, only the turbine V90-3.0 MW from Vestas was considered. For this model, c_1=9.4547 and c_2=1.7239.

The total power output of a wind farm with N WTG is:

$$P_{total} = \sum_{n=1}^{N} P_{g_n} \tag{13}$$

B. Collection System Design

Most of offshore wind farms are connected in a string arrangement, i.e. each row of turbines is connected between them and then to the substation. For internal connections, a medium voltage submarine grid between 25 kV and 40 kV is typically buried 1-2 metres deep in the seabed [15]. A joint of independent turbines is called cluster.

In this report, a string configuration with redundancy for the internal grid is considered. Some authors [16] state that clusters with redundancy, in spite of having higher internal grid electrical losses, may be an advantageous option, once they increment reliability. Therefore, since failure rates were assumed to be zero, a redundant network is considered. Fig. 4 represents this design.

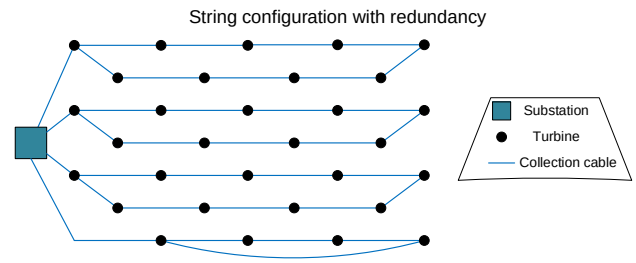

Fig. 4. String cluster with redundancy configuration implemented.

The active power losses depends on cables resistance and current. So, the cable electrical resistance, R, in ohms per metre is given by:

$$R = \frac{\rho}{S_c} \tag{14}$$

where ρ is the conductor resistivity (Ω.m) and S_c is the cable cross section (m^2). To calculate the rated current of a cluster, $I_{R_{\text{cluster}}}$, Joule's law is applied:

$$I_{R_{\text{cluster}}} \geq \frac{N_{\text{cluster}} P_R}{\sqrt{3}.U} \tag{15}$$

where N_{cluster} is the number of turbines in the cluster and U is the collection system line-to-line voltage. To simplify, all the cables from a given cluster have the same characteristics (except length).

C. Power Losses

The power flow for the entire wind farm internal network is solved by Matpower [17] which is a package of Matlab M-files for solving power flow problems.

The power flow is described by a complex non-linear equation system given by:

$$\left[\left(\frac{\bar{S}}{\bar{V}}\right)^*\right] = \left[\bar{Y}\right]\left[\bar{V}\right] \tag{16}$$

where $\left(\bar{S}/\bar{V}\right)^*$ is the injected current matrix and $\bar{V}$ is the complex voltage matrix. Once it is a non-linear system, it is computationally solved using an iterative method. Along the iterations, the slack bus voltage and the injected active power (because reactive power is considered to be zero) in PQ buses are kept constant. When the iterative process converges, all the voltages and the injected complex power in the slack bus are known and it is possible to calculate the branches (cables in the WFLOP) losses.

Cables are interpreted as a π system line (Fig. 5) [18].

Let i and j be two arbitrary buses connected. The injected current from i to j, $\bar{I}_{ij}$, is given by:

$$\bar{I}_{ij} = \bar{I}_L + \bar{I}_T \tag{17}$$

where $\bar{I}_L$ is the longitudinal and $\bar{I}_T$ is the transversal components of the line complex current, respectively. These components are computed using:

$$\bar{I}_L = \frac{\bar{V}_i - \bar{V}_j}{R + j\omega L} \tag{18}$$

$$\bar{I}_T = j\frac{\omega C}{2}\bar{V}_i \tag{19}$$

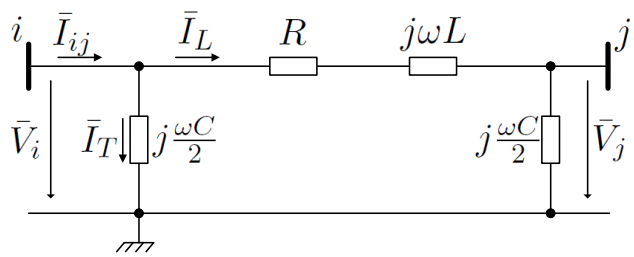

Fig. 5. π system line. R, L and C are the longitudinal line resistance, inductance and transversal capacitance, respectively.

The active power losses in a branch from bus i to j is the power dissipated in resistance R. Therefore, the total electrical losses, in a three-phase system are:

$$P_{loss_{ij}} = 3R.I_L^2 \tag{20}$$

where I_L is the RMS value of $\bar{I}_L$.

Now supposing that the cluster cable is always equal, the total electrical losses in a cluster cable are given by:

$$P_{loss_c} = 3R.I_L^2.l_c \tag{21}$$

where l_c is the total cluster cable length, considering tower's height and sea depth. For C clusters, the total power losses in a wind farm is:

$$P_{loss_{total}} = \sum_{c=1}^{C} P_{loss_c} \tag{22}$$

D. Energy Model

The generated power by WTGs depends on wind speed and direction and the electrical losses depend on the power produced. So, for a certain wind speed and direction we will have certain $P_{total}(u)$ and $P_{loss_{total}}(u)$. Lets consider that for an year, we have W wind samples. The AEP of the wind park is:

$$\text{AEP} = \frac{8760}{W} \sum_{w=1}^{W} P_{total}(u_w) - P_{loss_{total}}(u_w) \tag{23}$$

IV. Optimization Algorithms

Optimization algorithms can be divided in two categories: deterministic and probabilistic [19]. The former will search for every possible solutions and select the optimal one, while the latter is an iterative method that only computes a small number of solutions in each iteration, but trends to a maximum or a minimum with time. Once the WFLOP includes several design variables, the deterministic algorithm becomes unfeasible due to higher CPU times needed to search all possible solutions. The complexity and consequent CPU time of probabilistic algorithms are also dependent of the number of variables but they can perform significant better CPU times presenting results very close (or identical) to the deterministic value. The probabilistic optimization algorithms considered and implemented in this report are the Genetic Algorithm (GA) and the Particle Swarm Optimization (PSO).

A. Genetic Algorithm

GAs are Evolutionary Algorithms (EAs) and were designed to mimic the natural selection of species and the reproduction of the best fitted individuals from a population. They consist of a population transformed by three genetic operators: selection, crossover and mutation [20].

In each generation, individuals are ordered according their fitness and then the best fitted is selected to integrate the next population. A percentage of the remaining individuals (crossover percentage, P_{cross}) will be selected for the breeding process and the others are discarded. A P_{cross} of 80% is considered in this report because crossover operation is the main responsible for the "local evolution" of the population. If a low P_{cross} is considered the population will soon get "sterillized" and will probably converge to a local optimum.

After the selection process is complete, the breeding individuals will cross genetic information between them. A scattered crossover [20] with 50% from each parent is applied, i.e. each child receives half of its genes from one parent and the other half from another. Scattered crossover operation is displayed in Fig. 6.

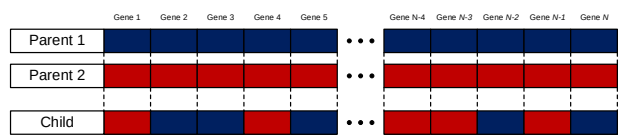

Fig. 6. Scattered crossover for a general case with a genome length of N (in the WFLOP, for a wind park with N turbines).

According to Safari et al. [21], a Darwinian interpretation on selection for crossover generates positive results, i.e. the most fitted individuals are more likely to transmit genetic information. In this report, a slightly different approach was taken: probabilities are neglected and it is assured that the most fitted individual (after the elite one) will mate with all the other individuals, generating one offspring in each operation. The selection and crossover operations are represented in Fig. 7.

A mutation is a simple modification in the genetic code, when a mutation occurs, only one gene is changed. Before the next generation is ready, it is submitted to the mutation operation. Mutation may or may not occur, its occurrence probability is called mutation probability, P_{mut}, and it should be kept low [22], since a high P_{mut} would make the algorithm tend to a random search [10]. Nevertheless, mutation operation is substantial as it allows the creation of individuals which are different from the individuals in the previous population [22] thus introducing new zones of possible good solutions and preventing the algorithm to fall into a local optimum value [23]. In this report, a P_{mut} of 0.1 is considered.

In the WFLOP, layouts represent individuals, genes represent turbines position and a mutated gene represents a turbine changing position.

B. Particle Swarm Optimization

Particle Swarm Optimization (PSO) was inspired in some of these species behaviour such as fish schooling and bird

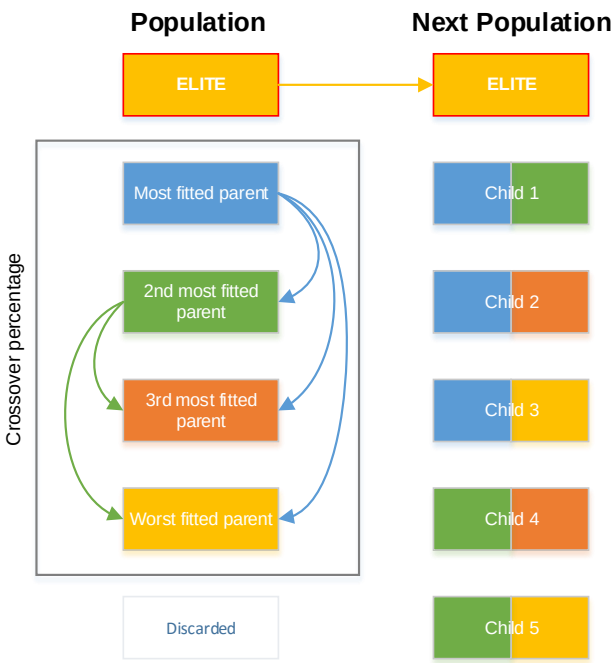

Fig. 7. Selection and crossover operations scheme for implemented GA considering a population with 6 individuals.

flocking [12]. The algorithms consists in randomly displaying particles inside a hyperspace (possible solutions) and then assigning them velocities. Once it is an iterative process, in every iteration each particle adjusts its "flying" according to its own flying experience (self-awareness) and its companions' (swarm) flying experience (social awareness). The PSO implemented in this study is an improved version proposed by Clerc et al. [24]. As stated in [25], particles moves are influenced by three components:

- *Physical component*: the particle tends to keep its current direction of displacement (also known as inertia);
- *Cognitive component* the particle tends to move towards the best site that it has explored until now;
- *Social component*: the particle tends to rely on the experience of its congeners, then moves towards the best site already explored by its neighbours.

Let the best known position of each particle i be $pBest_i$ (personal best) and the best known position of all particles be the *gBest* (global best). Each particle velocity and position in the next iteration is given by (24) and (25), respectively:

$$v_i^{k+1} = \Psi \left[C_{\text{phy}} + \psi_1 \text{rand}_1 C_{\text{cog}} + \psi_2 \text{rand}_2 C_{\text{soc}} \right] \tag{24}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{25}$$

where, C_{phy} is the *physical component*, C_{cog} is the *cognitive component* and C_{soc} is the *social component*:

$$C_{\text{phy}} = v_i^k$$

$$C_{\text{cog}} = \left(pBest_i^k - x_i^k \right) \tag{26}$$

$$C_{\text{soc}} = \left(gBest^k - x_i^k \right)$$

PSO terms are explained in TABLE I, furthermore, according to Clerc et al. [24], ψ_1 and ψ_2 should be related such as: $\psi_1 + \psi_2 = 4.1$.

TABLE I
PSO FORMULA TERMS MEANING.

Variable	Meaning
k	current iteration
$partNum$	Number of particles
i	particle, $i \in [1, partNum]$
v_i^k	velocity of particle i at iteration k
Ψ	Constriction coefficient
$\psi_{1,2}$	cognitive and social learning factors, respectively
$\text{rand}_{1,2}$	random values in the range of [0,1]
x_i^k	position of particle i at iteration k
$pBest_i^k$	particle i best know position until iteration k
$gBest^k$	global best know position until iteration k

The constriction coefficient is given by:

$$\Psi = \frac{2}{\left| 2 - (\psi_1 + \psi_2) - \sqrt{(\psi_1 + \psi_2)^2 - 4(\psi_1 + \psi_2)} \right|} \tag{27}$$

On one hand, *cognitive* and *social component* are responsible for intensification, i.e. they explore known "regions" while, on the other hand, the *physical component* is responsible for diversification once it forces the particle to search new "regions".

V. RESULTS

First of all, it is required to define the micro-siting criteria. In this report was considered that each turbine should be contained in a relatively large cell divided into multiple sub-cells. Then, the wind generator is to be placed in the centre of one of the sub-cells. This will make it possible to achieve optimum results while maintaining the traditional disposal with its inherent installation advantages. Turbines distribution per each cells is done traditionally and with an offset perpendicular to the prevailing wind direction (e.g. Kentish Flats, Barrow and London Array wind parks in United Kingdom [26]) as represented in Fig. 8.

The goal of this report is to maximize the AEP by placing the WTGs in the right sub-cells considering both wake losses and electrical losses.

The practical results from the present work are divided in two distinct subsections. First, the implemented GA and PSO are validated through statistics of 100 less complex runs of each technique. Secondly, the results of a case study considering more turbines, thus more complex, is presented. The wind data profile was kindly provided by WavEC[1] and, for the first case, consists in samples of the average wind speed and direction for 24 hours and, for the second case, samples of the average wind speed and direction for 3 hours. In both cases an year of production was considered.

[1]WavEC is deeply acknowledged for providing wind data.

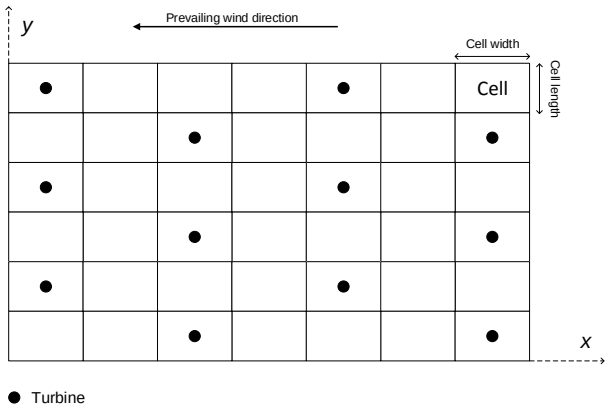

Fig. 8. Conventional layout with an offset.

A. GA and PSO Validation

To validate proposed resolution method for a problem, it is needed to know the solution. Hence, a deterministic algorithm to determine the best turbine disposal of a wind farm with 8 turbines and 4 sub-cells. Fig. 9 and TABLE II present the deterministic results.

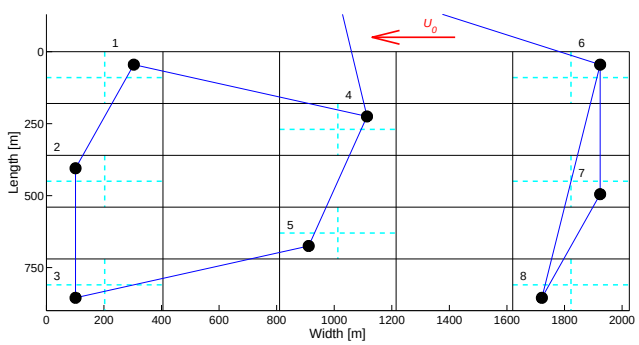

Fig. 9. Optimum layout determined by deterministic method. In spite of its consideration, to simplify the figure, substation isn't showed.

TABLE II
DETERMINISTIC ALGORITHM RESULTS.

Annual Energy Production [GWh]	**Turbines Energy Production** [GWh]	**Electrical Energy Loss** [MWh]	**Iterations**
58.107	58.212	105.533	65,356

Both GA and PSO were run 100 times in order to infer statistics about each one of them. The same stop criteria was considered for both algorithms, when the best solution is the same for 30 iterations, the algorithms stops and assumes the best solution until the moment as the optimal solution. It were considered 20 individuals and 20 particles for GA and PSO, respectively. Statistics are displayed in TABLES III and IV.

B. Case Study

In order to apply the developed optimization methodologies to a more realistic wind park, an 18 WTGs wind park was considered, whose characteristics are presented in TABLE V:

TABLE III
GENETIC ALGORITHM STATISTICS OF THE 100 RUNS.

GA statistics	
Best result	58.107 [GWh]
Worst result	58.034 [GWh]
Average result	58.091 [GWh]
Standard deviation	0.023 [GWh]
Deterministic layout matches	54/100
Average number of iterations	44.050
Total CPU time	2.053 [hours]

TABLE IV
PARTICLE SWARM OPTIMIZATION STATISTICS OF THE 100 RUNS.

PSO statistics	
Best result	58.107 [GWh]
Worst result	57.894 [GWh]
Average result	58.056 [GWh]
Standard deviation	0.052 [GWh]
Deterministic layout matches	12/100
Average number of iterations	37.870
Total CPU time	1.765 [hours]

TABLE V
PROPOSED WIND FARM MAIN CHARACTERISTICS.

Site		
Park total area	459.27	[ha]
Park length	1620	[m]
Park width	2835	[m]
Cells		
Cell length	180	[m]
Cell width	405	[m]
Cables		
Cross section	400	[m^2]
Rated current	590	[A]
Turbines		
Number of WTGs	18	
Model	Vestas V90-3.0 MW	
Rated power	3	[MW]
Rotor diameter	90	[m]
Hub height	95	[m]
Cut-in speed	3.5	[m/s]
Cut-out speed	25	[m/s]
Rated speed	15	[m/s]

In the case study, only GA was considered once it proved to find better optimum results (TABLES III and IV). For the same wind farm specifications and wind samples, different number of sub-cells are considered and the results are displayed. TABLE VII displays the obtained AEP as a function of the

considered sub-cells and Fig. 10 the correspondent optimum layouts are presented. The GA parameters considered are not the same for every number of sub-cells adopted once the problem complexity changes and TABLE VII shows it. Fig. 11 displays the evolution of population fitness for the 25 sub-cells most complex example.

TABLE VI
GA PARAMETERS FOR DIFFERENT NUMBER OF SUB-CELLS.

Number of sub-cells	Population Size	Iterations without improvement
4	40	35
9	60	40
16	80	45
25	100	50

TABLE VII
AEP AND ELECTRICAL LOSSES AS FUNCTION OF THE NUMBER OF SUB-CELLS.

Number of sub-cells	AEP [GWh]	Electrical losses [MWh]	Iterations
No sub-cells	141.294	327.726	-
4	142.361	334.594	41
9	142.574	331.651	148
16	142.932	332.927	157
25	143.041	335.827	210

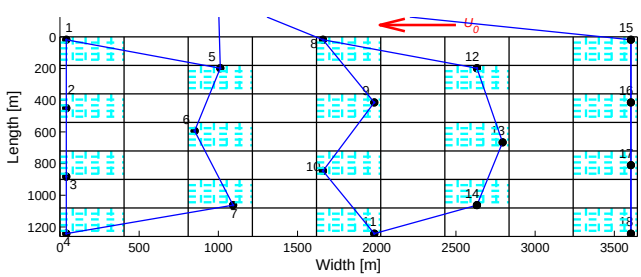

Fig. 10. Optimum layout for the case study with 25 sub-cells.

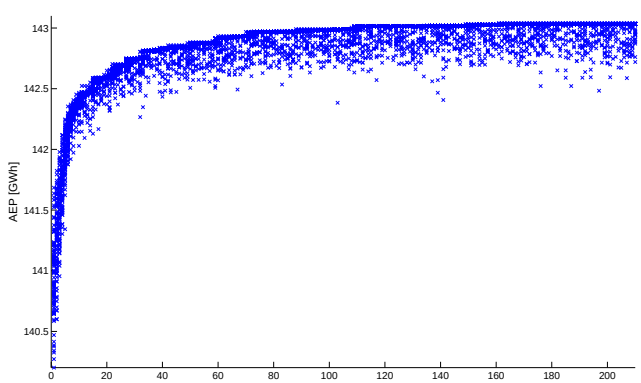

Fig. 11. Individuals fitness value evolution for 25 sub-cells approach.

VI. CONCLUSION

The WFLOP applied to offshore wind power output maximization has been addressed in this research. This is an important issue, since offshore wind power is still expensive and maximizing AEP is a major contribution to reduce the LCOE. AEP maximization is obtained by reducing all kinds of losses inside the park. In this research, only wake and internal network electrical losses have been considered, because these are among the most significant ones.

Concerning the algorithms validation, it should be mentioned that GA reaches the deterministic result in 54% of the runs, while PSO hits 12%. It also can be inferred that PSO is faster once it founds the optimal value after an average of 38 iterations (CPU time near 1.8 hours), while GA takes an average of 44 iterations to find the optimal value (CPU time near 2.1 hours). Therefore, one can conclude that PSO is more efficient, meaning that it is faster to reach a good result approximation, while GA is more effective, meaning that it finds a good result approximation more often. The comparison resulted favorable, because both optimization algorithms reached the optimal AEP as calculated by the deterministic technique, within a very small tolerance, and, most important, reducing CPU time from 150 hours to 2 hours.

Furthermore, the results obtained demonstrated that GA is able to reach better solutions than PSO. It is true that the latter converges to an optimum value in fewer iterations (reduced CPU times) but it gets easily "traped" in local optimum being more ineffective in searching new optimal zones. On the other hand, once GA reaches a local optimum, the genetic operator mutation helps the algorithm to find solutions away from the current search zone, therefore enabling to find new best solutions.

Then, a more realistic case-study (18 WTGs wind park) was implemented and assessed. In this case, the influence of the number of sub-cells is apparent, the higher the number of sub-cells is, the better the AEP obtained. On the other hand, the AEP increase reduces with the number of sub-cells. This means that, at some point, extend the problem complexity (i.e. adding more sub-cells) will not pay the results obtained, because the AEP will not increase significantly. The CPU time also increases much due to the addition of individuals to the population and because the convergence criteria is computational heavier (TABLE VI).

An AEP increase of 1.24% was obtained when using the best micro-siting approach proposed (25 sub-cells inside major cells). This increment may be even more significant if the micro-siting approach is used after an optimization of the cells dimensions.

Overall, the proposed optimization concept and turbines positioning is very realistic and project friendly, as the WGTs are restrained to a small area (when compared to the entire wind park area) favouring the wind farm construction, not only the turbines and foundations, but mainly the submarine cable laying.

ACKNOWLEDGMENT

The author would like to thank to his supervisor Prof. Rui Castro, WavEC and EDP Inovação for the knowledge sharing

and the data kindly supplied and to all the researchers who had a role in the development of this report.

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