

# Improved Design of a Large Offshore Wind Farm by Using Biogeography based Optimization

Mohammed Amine Hassoine \*‡, Fouad Lahlou \*, Adnane Addaim \*\*, Abdessalam Ait Madi\*\*\*

\* Faculty of Sciences, Ibn Tofail University, 14000 Kenitra, Morocco

\*\* Mohammadia School of Engineers, Mohamed V University, Rabat, Morocco

\*\*\* Advanced Systems Engineering Laboratory, National School of Applied Sciences, Ibn Tofail University, 14000 Kenitra, Morocco

(mohamedamine.hassoine@uit.ac.ma, fouad.lahlou@uit.ac.ma, addaim@emi.ac.ma, abdessalam.aitmadi@uit.ac.ma)

‡ Corresponding Author; mohamedamine.hassoine@uit.ac.ma

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**Abstract-** This paper investigates optimal placement of wind turbines (WTs) within a large offshore wind farm (LOFWF). 88 wind farm (WF) configurations are investigated to search the optimal layout for the Horns rev 1 offshore WF using twenty years of wind data knowing that wind characteristics are modeled from long term reanalysis data based on MERRA-2. The regular and the irregular placement of the Horns Rev 1 (HR1) offshore WF are investigated with Jensen wake model. Therefore, the objective is to assess the effect of wind turbine spacing (WTS) on the power output loss in a LOFWF and, also to find the best configuration that gives the maximum power with minimum investment cost. The use of the Biogeography based optimization (BBO), as a bio-inspired evolutionary approach, represents the advantage of being effective on strongly non-convex spaces such as a large offshore WF. Due to the iterative process applied to the initial population, and the multiplicity of the population, the BBO process limit the risk of getting stuck in a local optimum, by distributing the individuals in the whole solution space. The results obtained show that the wind data extracted from MERRA-2 can be applied reliably to any existing WF to simulate wind power production. The results also demonstrate that significant power losses occur when the turbines are arranged in a condensed manner and the significant power gains are not obtained from too large configurations, but rather from the best placement in configurations. The proposed approach shows promise in terms of applicability with MERRA-2 and is effectively suitable for arranging turbines and assessing wind resources in an offshore wind farm project (OFWFP).

**Keywords** Biogeography based Optimization; Layout Optimization; Offshore wind farm; Wake model, Wind turbines.

## 1. Introduction

WTs are organized into an offshore wind farm (OWF), which includes a set that goes from a few units up to almost two hundred WTs. The offshore wind farm is scattered at sites carefully selected based on wind potential. To maximize the electrical energy produced by a WF, WTs should be spaced in the direction of the prevailing winds, so that they can continue to receive strong winds.

The investigation design of an OWF requires knowledge of local wind conditions. For this type of problem, it is necessary to predict the wind potential [1]. One of the most well-known solutions is the use of MERRA-2 [2]. MERRA-2

is a global atmospheric reanalysis produced by the NASA CMMS (Global Modeling and Assimilation Office) [3].

Recently, the MERRA and MERRA-2 are widely used to simulate wind power production. Numerous studies have been conducted to assess the applicability of MERRA-2. Staffell et al. [4] were the first who validate MERRA-2 for wind power in 23 European countries in 2016. Olauson et al. [5] modeled wind power potential in Swedish by using MERRA in 2015. Cali et al. [6] analyzed the potential locations for offshore WFs in Turkey using MERRA in 2018. In 2020, Yue et al. [7] have used MERRA data in comparison to floating LiDAR device and mast to assess wind resources and optimize the layout of the Changhua-Sud OWF.

Optimizing the placement of WTs within the OWF has been resolved for many years. This optimization is known as the WF layout optimization problem (WFLOP). Some typical work using an approach based on genetic algorithms was performed by Mosetti et al. [8], Grady et al. [9], Emami et al [10], as well as Mittal [11], Rajper [12] and Hassoine et al [13, 14]. Using the same models of the WF and cost, Wan et al. [15] and Pookpant [16, 17] demonstrated the optimal placement using Particle Swarm Optimization to maximize power production. Bansal [18] and Pouraltaf et al. [19] use BBO for solving WFLOP.

In this article, we use the HR1 OWF farm in Denmark: Firstly, to carry out a study to evaluate the impact of OWF size on power output, and secondly to optimize the layout of the WF using a BBO algorithm for two reference spaces. The simulation results indicate that the proposed method is capable to find the best layouts that surpass the current design by increasing power and efficiency in a reasonable area.

The rest of this article is organized as follows. Horns Rev1 offshore WF, data source, models and wind characteristics are first presented in section 2. The impact of offshore WF size on power output are discussed in section 3. In section 4, OWF Layout optimization process is presented. The results of the two optimized cases are presented and discussed in section 5. Section 6 presents the conclusions.

## 2. Offshore Wind Farm models and Data Source Description

### 2.1. Horns Rev1 Offshore Wind Farm

Horns Rev 1 is an LOFWF located on a shoal zone in the east of the North Sea about 14 km from the west coast of Denmark as seen in Figure 1. It is composed of 80 WTs of 2 MW each manufactured by Vestas. The turbines are spread over an area of 5km x 3.9km. The wind park is arranged in a regular layout in eight lines and ten columns forming a parallelogram with a short side inclined by 7 degrees relative to the north-south direction.

The spacing of the turbines within the wind farm varies according to the direction. The distance is 7D (560 m) for the two sides of the parallelogram aligned respectively at 270 ° and 353 °. For the first diagonal the distance is 9.4D (750 m) and is aligned at 221 °. For the second diagonal the distance is 10.4 D (833 m) and is aligned at 312 °. The latitude and longitude coordinates of Horns Rev 1 are respectively 55° 30' 11.52" N and 7° 47' 46.931" E. It was the first largest OWF in the world in 2002 with an installed capacity of 160 MW. The numbers from 1 to 80 are used in the numbering scheme as seen in Figure 2.

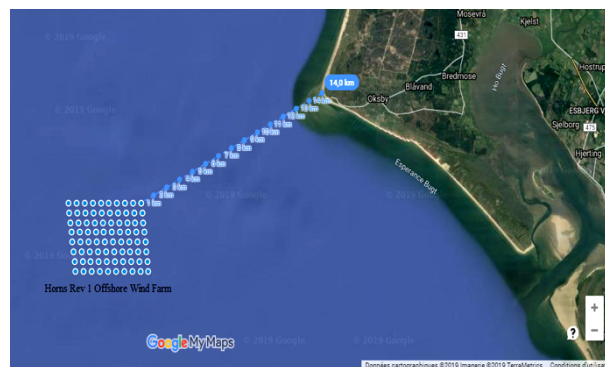


Fig. 1. Map of HR1.

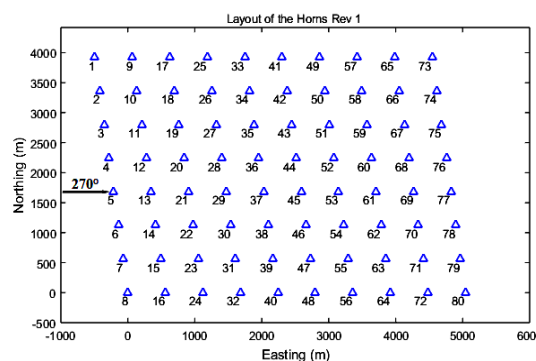
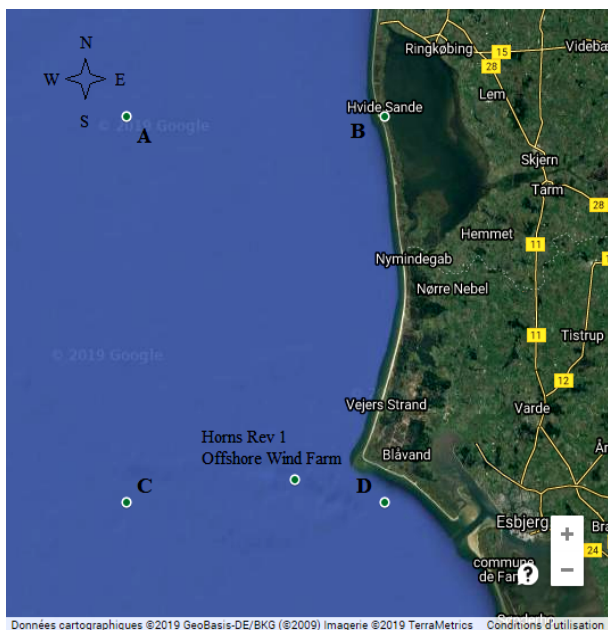


Fig. 2. Numbering scheme of HR1.

### 2.2. Wind Data Source Description and Wind Characteristics

The materials and mechanisms of a wind turbine [20, 21] are exposed to winds and bad weather and are subject to strong physical constraints. WTs become brittle, which reduces performance and safety. The lifespan of a wind farm is estimated at 20 years [22, 23].

Twenty years (1999-2019) of wind speed and direction is taken from the MERRA-2 dataset. The MERRA-2 reanalysis data of long-term datasets are meteorological data taken from meteorological assimilation models, and which have been reworked to ensure long term stability and consistency. MERRA-2 has a sufficiently long history of these data, and it is available from 1980 to the present. The data are available on regular grids, the spatial resolution of which can be 0.5° × 0.625° (lat x lon), with a spacing of about 55 km for some locations. The MERRA-2 points surrounding Horns Rev 1 are shown in Figure 3 below.



**Fig. 3.** Horns Rev 1 and MERRA-2 grid point.

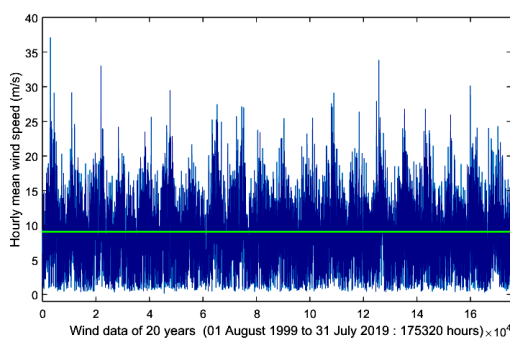
The spatial interpolation is used to predict the value of the wind speed at the position of HR1 offshore wind farm. This process consists of using points with known values for estimated values at other unknown points. Spatial interpolation can estimate wind speed and direction at locations without recorded data of MERRA-2 by using known values in nearby to geographic coordinates of a wind park. We used here the Inverse Distance Weighting (IDW) interpolation method [24, 25] in which sample points are weighted during interpolation in such a way that the influence of one-point relative to other declines with the distance from the unknown point.

The hourly wind data (20 years) from the four surrounding MERRA-2 grid points (A, B, C, and D) (see Figure 3) is used for forecasting hourly wind [26] data of 20 years for Horns Rev1. The wind speed is extrapolated to the hub height of the WTs using the power law [27]. The coordinates of the surrounding point and Horns Rev1 are shown in Table 1.

**Table 1.** MERRA-2 grid point and Horns Rev1 offshore wind farm coordinates.

Reference	Latitude	Longitude
Horns Rev 1	55° 30' 11.52" N	7° 47' 46.931" E
MERRA-2 A	56° N	7° 30' E
MERRA-2 B	56° N	8° 7' 29.999" E
MERRA-2 C	55° 30' N	7° 30' E
MERRA-2 D	55° 30' N	8° 7' 29.999" E

Figure 4 shows the hourly average wind speed (averaging 175,320 hours) (20 years) at 50 meters, with an average of 9.05 m / s marked by a green line. This wind speed is perfectly suitable for energy production.



**Fig. 4.** Wind speed in Horns Rev1, from 01 August 1999 to 31 July 2019.

The number of hours during which the wind has blown at a given speed makes it possible to calculate the parameters of the Weibull curve which characterizes the distribution of wind speeds over the HR1. Similarly, for each sector of geographical orientation, the number of hours during which the wind was oriented according to this one makes it possible to obtain the site's wind rose (frequency of wind speeds according to each orientation sector).

Therefore, we have for the sites a compass rose as well as an estimated Weibull curve. Regarding the Weibull law, the estimation of the parameters is particularly important to find the values of the scale parameter (c) and the shape parameter (k) in such a way that the Weibull function fits best the available wind data. For our case study, we applied the graphical method [28, 29].

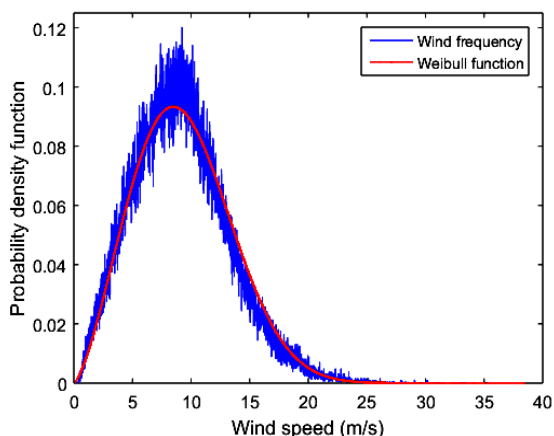
The Weibull parameters and mean speed of Horns Rev 1 and MERRA-2 grid points are represented in Table 2. The average wind speed at an altitude of 50 meters is 9.05 m / s, and becomes 9.36 m/s at the height of the hub. This average is in perfect agreement with an average of 10 m/s stated by the owner of the HR1 (Vattenfall, owner of 60%) [30].

**Table 2.** Weibull parameters and mean speed in Horns Rev 1 and MERRA-2 grid point.

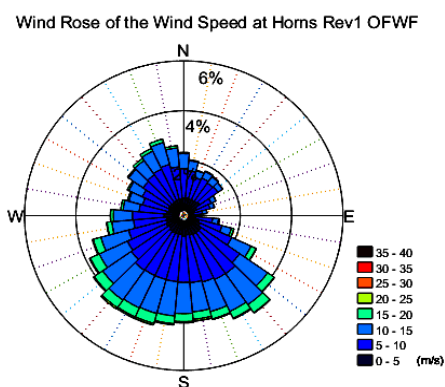
Parameters	Hub Height (m)	Weibull Parameters		mean speed (m/s)
		k	c	
MERRA-2 A	50	2.2189	10.2074	9.0402
MERRA-2 B	50	2.2542	9.6893	8.5822
MERRA-2 C	50	2.2126	10.2619	9.0884
MERRA-2 D	50	2.2177	9.7130	8.6024
Horns Rev 1 OFWF MERRA-2 (interpolated)	50	2.4258	10.2157	9.0579
Horns Rev 1 OFWF MERRA-2 (extrapolated)	70	2.4258	10.5652	9.3678

The adjustment by the Weibull distribution is performed from the hourly data of wind speed for twenty years (1999 to 2019). The values of the Weibull parameters are calculated ( $k = 2.4258$  and  $c = 10.21$  m/s) at 50 m from sea level with an average wind speed of 9.05 m/s. Wind speeds frequency and the Weibull distributions of Horns Rev1 are shown in Figures 5. The predominant site speeds vary between 7.5 m/s and 12.5 m/s.

Figure 6 shows the distributions of wind speed and its direction from 1999 to 2019. The probabilities for the direction sectors are visualized for grouped data into 36 direction sectors. We notice that the prevailing winds come mainly from the southwest during the considered period.



**Fig. 5.** Wind speeds frequency and the Weibull distributions of HR1.



**Fig. 6.** Wind rose of wind speed of HR1.

### 2.3. Wake effect and Cost Model

The WT derives its energy from the kinetic energy of the wind which depends on the mass and speed of the wind. The WT recovers this kinetic energy by slowing the wind in the space determined by the surface of its rotor. Betz's law determines that a WT can never convert more than 16/27 (or 59%) [31] of the kinetic energy into mechanical energy. When wind flows through the rotor of a wind turbine, the wake expands with down-stream distance, the wake model used here is a Jensen model [32, 33]. the wake expands linearly as a function of the distance crossing by the wind. The power generated by the WT can be expressed by the following formula, given by equation (1):

$$P_{wt} = \frac{1}{2} \eta \rho A u^3 \tag{1}$$

with  $P_{WT}$  is the power,  $A$  is the area of the circle with a radius equal to the length of a blade,  $u$  is the wind speed,  $\eta$  is the efficiency of WT and  $\rho$  is the density of the air.

When a site is composed of several WTs, the power of the WF is calculated by the following equation (2):

$$P_{wf} = \sum_{i=1}^N P_i \tag{2}$$

where  $N$  is the number of WTs and  $P_i$  is the power of the  $i$ -th turbine.

The efficiency of the wind farm is expressed in the form of a ratio between the power of the WF and the sum of the powers of the WTs taken one by one without a wake effect. This efficiency is expressed using the equation (3):

$$\eta_{wf} = \frac{P_{wf}}{\sum_{i=1}^N P_{si}} \tag{3}$$

with  $P_{si}$  is the power of the  $i$ -th turbine if it is functioning as a single WT.

The annual Energy Production (AEP) consists of estimating the annual electricity production of different wind turbines on the same site for one year. 100% availability is assumed for this estimation. The capacity factor is the ratio between the annual production and the rated production [34] of a WT. The hours of operation are the number of hours per

year that the WT produces electricity. The number of hours in a year is 8760.

The AEP can be calculated by equation (4) [35]:

$$AEP = T \sum_{i=1}^{directions} \sum_{j=1}^{speed} \sum_{k=1}^{turbines} f_{ijk} P_{ijk} \quad (4)$$

where,  $f_{ijk}$  is the frequency of the wind in direction  $i$ , with a wind speed  $j$  for wind turbine  $k$ ,  $T$  is the number of hours in the year and  $P_{ijk}$  is the power produced by WT.

The cost of an OWF depends on several parameters, such as distance from the shore, depth of water, and grid construction and connection. This cost is made up of the costs of the turbines, operating and maintenance costs, the cost of supporting the structure, plus the cost of connection to the network. The optimization of the WF is done to minimize the unit cost of energy. When calculating this Levelized cost of energy (LCOE), all the factors that make up the cost of a WF are taken into account while minimizing the objective function (cost per unit of power). The number of turbines is considered as the cost variable in the cost model. A cost function, called the E-RBF cost model, is developed by Zhang et al. [36]. The E-RBF is used for identical wind turbines. The cost model used to carry out this study is given by equation (5):

$$Cost_N(N) = 133.3938 - 0.1501N - 7.9 \times 10^{-4} N^2 \quad (5)$$

where  $N$  is the number of WTs on the WF.

The search for the optimal configuration of the OWF is carried out by an approach that aims to have a minimum cost per unit of the produced energy.

This optimization can be achieved by maximizing the power produced by the WF while minimizing its cost. The objective function is used as a fitness function which will minimize the cost per unit of the produced energy. The effective cost per Kilo Watt (KW) of the produced power can be expressed by equation (6):

$$Cost_{N,eff} = (Cost_N P_o N) / P_{farm} \quad (6)$$

with  $P_o$  is the rated power of the WT.

### 3. Impact of Horns Rev 1 Size on Power Output

In the WF design process, the ability to measure the spatial variability of turbine wakes and to assess its influence on power output variability is a fundamental step in the implementation of an approach for conducting the Offshore Wind Power Project. In this part, we seek to answer this question. The aim is to study the influence of the size of the WF on the power output. This consists of varying the turbine spacing in the prevailing and across the wind direction.

We have varied the size of the horns Rev1 by increasing gradually the distances between the rows and distances between the columns. The distance varies from 5D to 15D between the columns in the prevailing wind direction (PWD) and from 5D to 12D between rows in the across wind direction (CWD). Thus, we obtain 88 configurations in two

stages. In the first stage, we start by varying the distance between the rows (from 5D to 12D) and we keep that of the columns fixed. In the second stage, we vary the distance of the columns (from 5D to 15D) and we repeat stage one. Figure 7 shows the layout of the first configuration (CONF1) (5D5D) with a blue outline and, the layout of the last configuration (CONF88) (12D15D) with a green outline. Table 3 depicts the configuration number when CWD and PWD are selected.



Fig. 7. First and last configurations of Horns Rev1.

Table 3. Configuration number (CWD-PWD) of Horns Rev1.

PWD	CWD							
	5D	6D	7D	8D	9D	10D	11D	12D
5D	1	12	23	34	45	56	67	78
6D	2	13	24	35	46	57	68	79
7D	3	14	25	36	47	58	69	80
8D	4	15	26	37	48	59	70	81
9D	5	16	27	38	49	60	71	82
10D	6	17	28	39	50	61	72	83
11D	7	18	29	40	51	62	73	84
12D	8	19	30	41	52	63	74	85
13D	9	20	31	42	53	64	75	86
14D	10	21	32	43	54	65	76	87
15D	11	22	33	44	55	66	77	88

Horns Rev 1 is experienced by low turbulence (<8%) [37] with the ambient turbulence and Surface roughness values are 0.07 and 0.02, respectively. The Vestas turbine (V80 – 2 MW) is used in HR1. The thrust coefficient is

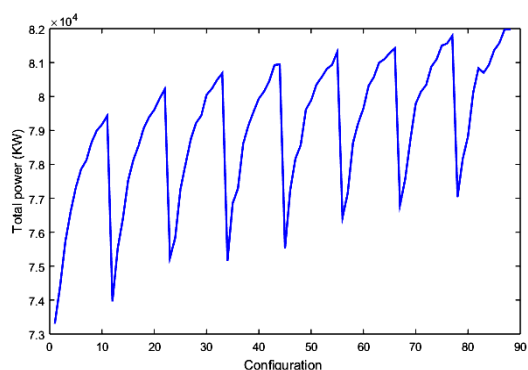


assumed to be constant for a speed of 8 to 9 m/s, with a value of 0.8065 [38]. Table 4 shows the technical characteristics of Horns Rev1 wind turbine [39].

**Table 4.** HR1 wind turbine specifications.

Parameters	Value
Wind turbine model	V80 – 2 MW
Rated power (kW)	2000
Cut-in wind speed (m/s)	4
Rated wind speed (m/s)	16
Cut-out wind speed (m/s)	25
Hub height (m)	70

To compute power output for all configurations, we have developed a MATLAB code. Figure 8 shows the power output evolution by each configuration. The Jensen model predicts a cyclical and increasing evolution of power. In fact, we can notice that each cycle has a rise, a peak, and a fall. The number of cycles represents the eight changes in distances between the rows (from 5D to 12D) and the increase is almost linear in the dominant direction (from 12D to 15D).



**Fig. 8.** Evolution of power output using 88 configurations of Horns Rev 1.

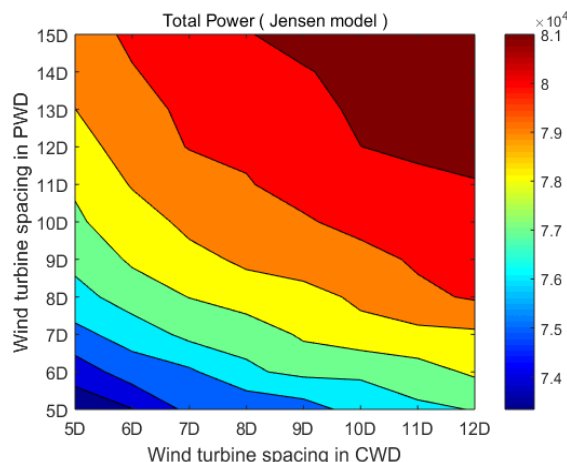
The area of the last configuration (10.8 km x 6.7 km) is seven times larger than that of the first configuration (3.6 km x 2.8 km), and almost four times the size of the actual Horns Rev1 area (5 km x 3.8 km). When the surface area varies from 10.08 km<sup>2</sup> (CONF1) to 72.36 km<sup>2</sup> (CONF88), a modest increase in power output is observed.

A comparison of power output for three configurations is shown in Table 5. The Jensen models show a power output growth of 11.77% (8638.62 KW).

**Table 5.** comparison of power output for three configurations.

Model	Calculated Power (MW)		
	5D5D	7D7D	15D12D
Jensen	73.33	77.26	81.97

Figure 9 shows the iso values of the power output as a function of the spacing in the two directions (CWD and PWD), the power output is characterized by zones of iso values of power which are separated by quasi-linear curves.



**Fig. 9.** Power output isovalues by spacing.

#### 4. Horns Rev 1 Offshore Wind Farm Layout optimization process

Optimizing the layout of the HR1 wind farm consists of finding the optimal positions of the turbines in a given area (search space), which minimize the effects of wake under the condition of maximizing the power and minimizing the cost. In this work, we propose the use of Biogeography-based optimization (BBO) for the best Offshore Wind Farm Design searching. In this paragraph, a description of the BBO process is presented.

BBO is a class of evolutionary algorithms that are based on the use of a population. The BBO approach is proposed by Simon in 2008 [40] and is inspired by the biogeography concerning the migration of species between different habitats. Biogeography-based optimization optimizes a problem by stochastically and iteratively improving candidate solutions with respect to an objective function (fitness). The optimization process begins with generating a finite number of selected individuals (habitats) by random selection in the search space forming the initial population. After evaluation of the initial population, certain individuals are chosen to participate in the migration operation which creates a new set of individuals. This step is stochastic and depends on the emigration and immigration rates of the individuals involved. The descendants will in turn be transferred. The mutation rate fixes the proportion of the population that will be renewed in each generation. Elitism allows the conservation of the best individuals found, as long as they are not overtaken by others. Finally, a replacement phase consists of replacing the parents with the new descendants in order to form a new population of the same size as at the start of the iteration.

Simon, in 2008 [40], demonstrated that BBO has had good convergence properties for different benchmark functions compared to other meta-heuristics such as genetic

algorithm (GA), ant colony optimization (ACO) and particle swarm optimization (PSO).

Knowing that the WF layout optimization problem has been resolved for many years by using GA, ACO and PSO approaches. We can conclude that BBO presents a very good alternative to solve WFLOP.

With the implementation of the BOO algorithm, two research areas are adopted; one is smaller, the other is bigger than the Horns Rev1 area. These areas are assumed to be square according to the Northing dimension (3,920 m), and the Easting dimension (5,040 m) with the minimum distance between two neighboring turbines is 400 m (5D). The search for optimal Layout is carried out by an iterative approach by developing a code in MATLAB using BBO.

The OWF receives a variable wind in speed and direction. The directions are divided into 36 sectors taking into account their probabilities. The calculation of the output power of the OWF requires the calculation of the speed of

each turbine. The quality of the Layout of the OWF is evaluated by the fitness value using equation (6).

Within an OWF, the positions of a number (N) of wind turbines are defined by two-dimensional coordinates (X, Y). The wind speed of each wind turbine is calculated using Jensen's wake model [32], and the superposition effect of several wakes upstream of each turbine is evaluated by using the sum of squares method, as shown in [33]. The power of each turbine and the output power of OWF are calculated using equation (1) and (2) respectively. The annual Energy Production is estimated by using equation (4).

The computing output results are the coordinates of turbines, the wind speed for each turbine, the power output, and the levelized cost (fitness) of Horns Rev 1 OWF. The process will be stopped when the best fitness keeps the same value for 500 generations. Figure 10 explains the optimization process. BBO parameters are presented in Table 6.

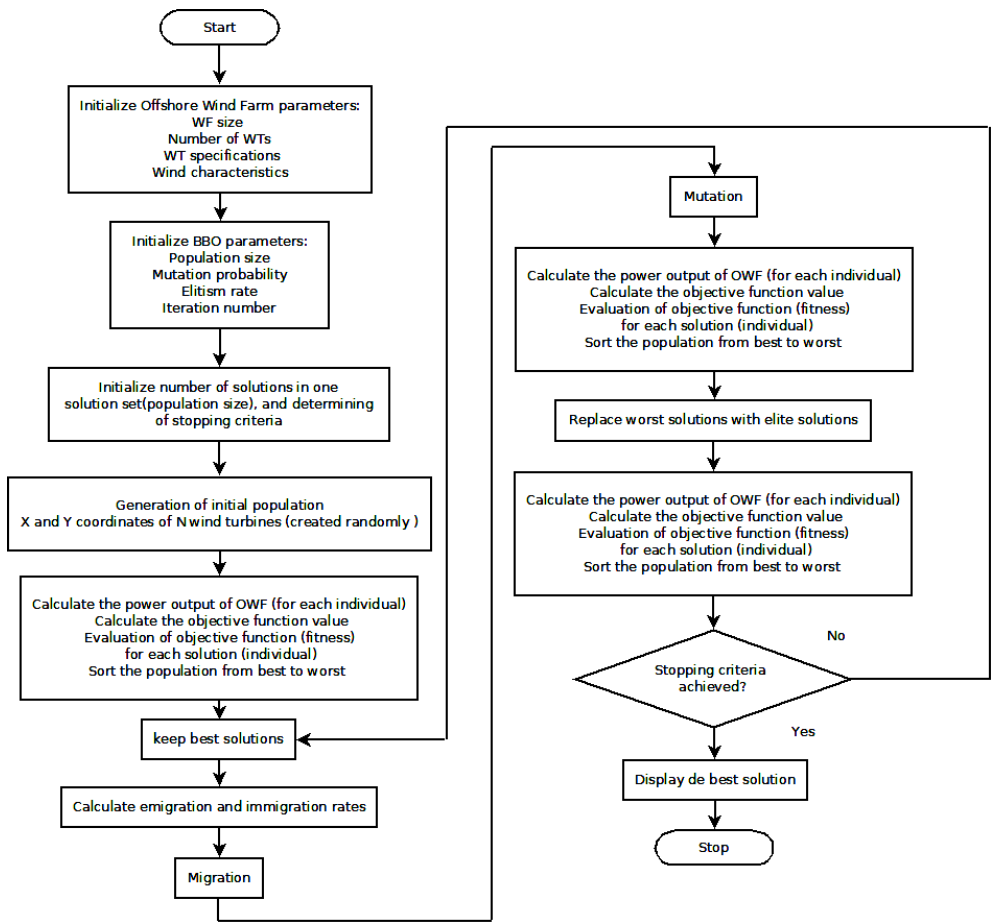


Fig. 10. Flowchart of the BBO optimization process.

**Table 6.** The parameters of BBO.

Parameters	Value
Population size	15
Mutation probability	0.01
Elitism rate	2
Iteration number	2000

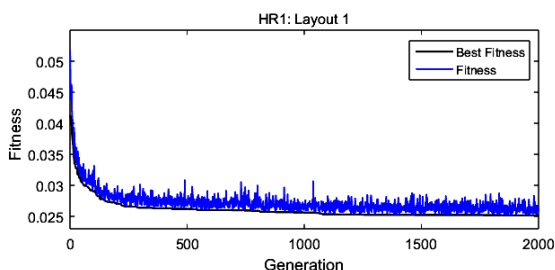
**5. Horns Rev1 Wind Farm Layout optimization result and discussion**

The BBO approach is implemented under 20 years of wind data (MERRA-2). The Jensen model is used for wake effect calculation. A population of fifteen individuals was introduced to evolve over 2000 iterations. After the execution of the BBO program on two research areas, two optimized layouts of the HR1 wind farm are obtained. For the first area, after 1253 iterations, the value of the best fitness remains almost constant and the best layout of 80 turbines is obtained for the best fitness value of 0.0251669 and the power output is 84,609.14 kW with efficiency of 52.88%. Figures 11 and 12 show respectively, the convergence curve of the fitness function and the evolution of power output for layout 1.

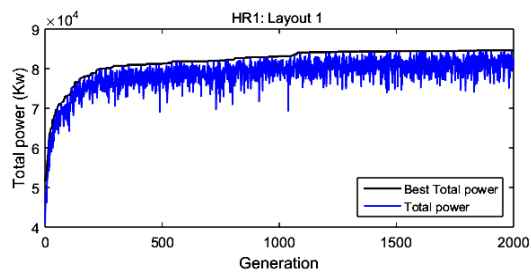
In the second area, the best layout for 80 wind turbines is achieved after 316 iterations with the best fitness value of 0.0249787 and the power output is 85,246.49 kW with an efficiency of 53.27%. Figure 13 and 14 show respectively, the convergence curve of the fitness function and the evolution of power output for layout 2. Table 7 shows a comparison between the two optimized layouts.

**Table 7.** Comparison of Layouts.

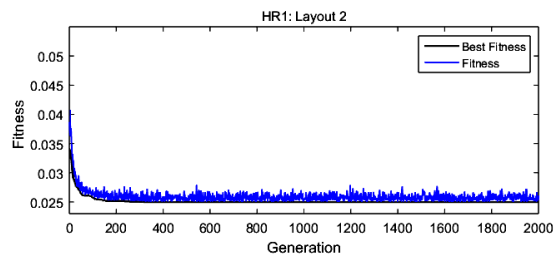
	Layout1	Layout2
Fitness value	0.0251669	0.0249787
Power output (KW)	84609.14	85246.49
Efficiency (%)	52.88	53.27



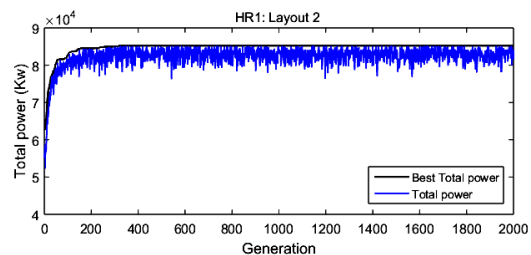
**Fig. 11.** Convergence curve of fitness for layout 1.



**Fig. 12.** Evolution of power output for layout 1.

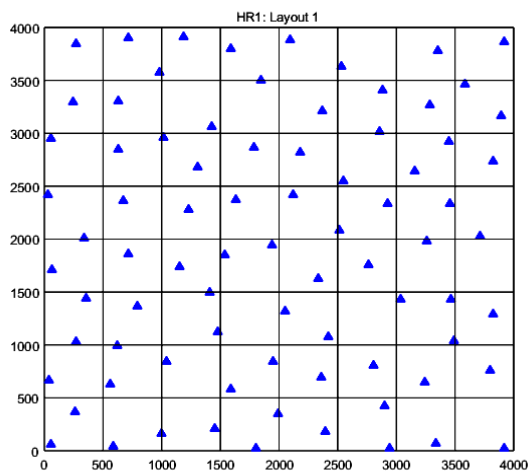


**Fig. 13.** Convergence curve of fitness for layout 2.



**Fig. 14.** Evolution of power output for layout 2.

Figures 15 and 16 show the optimal layouts of the first area and the second area.



**Fig. 15.** Optimal layout of the first area (layout1).



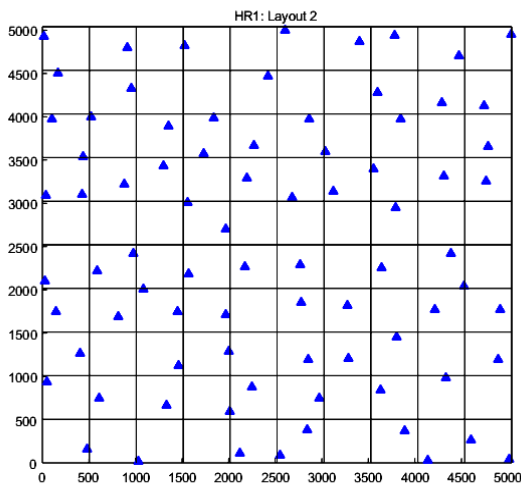


Fig. 16. Optimal layout of the second area (layout2).

To compare the positions of the turbines, the three layouts are drawn in Figure 17.

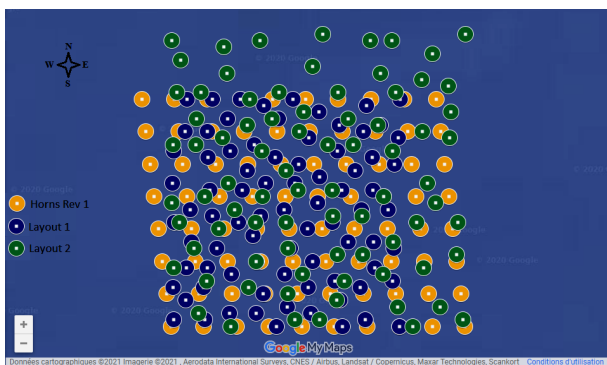


Fig. 17. Comparison of the positions of the turbines in three layouts of HR1.

The placement of the turbines is achieved by an irregular arrangement. This allowed minimizing the effects of wakes between the turbines in areas close to the size of HR1. So, in the irregular layouts, the results depend on how the turbines are arranged. In contrast, the widest arrangements give the best results for the regular layouts (see section 4). The two optimal layouts generate respectively a power output of 84,609.14 KW and 85,246.49 KW. These values are higher than the power output of configuration 88 (15D12D), which is calculated for the largest configuration (see Table 7). Therefore, the increase in the size of the offshore wind farm generates less profitable gain when the power output increases moderately. This is justified by the fact that the best recovery does not exceed 6% relative to the initial arrangement of Horns Rev1, and at the same time it generates additional connection costs when the area becomes four times larger. As a result, the best arranged offshore wind farm is better than the largest offshore wind farm.

## 6. Conclusions

Modeling efforts for the design of WFs in the preliminary project design phase are encountering difficulties

in estimating the best placement of turbines. Some differences observed between models and reality can be attributed to the complex unsteady phenomena that occur inside wakes of turbines in the Offshore wind farms. This article presents an approach to optimize the layout of offshore wind farms which consists of describing, formulating, and solving a layout problem. In particular, we have conducted a comparative study of WTs layout within an OWF using the Jensen wake model and biogeography based optimization. The power output of Horns Rev 1 OWF has been evaluated with 88 configurations by mean of hourly wind data based on 20 years of weather data (1999-2019) of MERRA-2 data. The complexity of a layout problem has also been discussed. We have investigated the regular layout and irregular layout of wind turbines within a large offshore wind farm, and the optimization solution in terms of choosing the best layout was given by the optimal solutions offered by a stochastic and iterative approach. We have applied a BBO algorithm approach to achieving the best placement of WTs in order to get the most out of the power output. The BBO algorithm combined with MERRA-2 can be considered as an effective methodology for the optimization of WF layout when offshore wind farms projects are concerned. In this article, the results obtained have provided a better understanding of the phenomena linked to the variability and interactions of wakes of turbines within an offshore wind farm, which could thus be better taken into account when designing wind farms. We can say that the BBO approach offers design alternatives that are better suited to the real conditions of existing offshore wind farms. In the ongoing research, we will take into consideration realistic wind conditions of the offshore wind farm and using more complex wake models such as computational fluid dynamics (CFD) based models.

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