

The reviewer strongly believes that the paper presents critical wind farm layout optimization aspects. The results appear original and very well written.

Page1: Title. While it is generally understood why the author is discussing wind farm layout, it might be clear to revise the title to explicitly mention "offshore" wind farm layout to clarify the study's focus, as offshore constraints differ widely from onshore. This would also improve clarity for future citations.

Page1: Line4. "to the authors' best knowledge" is unnecessary. It is expected that the author performs extensive research and could state that they performed an extensive literature review and did not find any prior studies on the topic.

Page1: Abstract. Generally, improve clarity in the abstract. For instance, when stating, "the contributions of this paper are twofold," explicitly mention the method – heuristics - rather than vaguely referring to it as a method to handle the optimization problem.

Page1: Line13. Provide reference to the claim in Line 13/14

Page3: Line60. Z^* is redundant. Not utilized in the rest of the paper

Page3: Line81. Clarify how the random wind variable was determined. Because the probability distribution of wind speed and direction were introduced on Page 4.

Page4-8: Study domain. Was a regularization term introduced to prevent overfitting specific wind conditions for wake? How will this change the result?

Page5: Line116. θ_1 is a constraint as provided in Fig1, which means the wind farm is constrained to θ_1 between -90 and 90 . Are wind farms never aligned outside these angles? See comments on Fig7.

Page5: Line18. D_{min} and D_{max} are not specified as a multiplication of rotor diameter. Some wake models utilize $5D$, $6D$, $7D$ etc of the rotor diameter (D)

Page8: Line184. The authors compare their case study to Thomas et al. (2023) DEBO algorithm, but they do not provide a direct numerical comparison of the results

Page14: Line246. The conclusion claims that their proposed method outperforms a baseline but does not specify by what percentage.

General comments:

The heuristic model lacks sufficient detail in the explanation. Because it did not compare with the baseline models to see how they outperformed the others.

Results lack error analysis, confidence intervals, or sensitivity to other wake model assumptions.

Basic explanations for the choice of constraints made are generally not provided. For instance, how does reducing Δr (grid spacing) affect AEP and computational cost?



offshore wind

Wind farm layout optimization with alignment constraints

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Abstract. Wind farm layout optimization involves placing wind turbines in a defined domain to minimize the expected production losses due to wake effects within the wind farm. Because of navigational regulations, tenders for offshore wind farms often impose so-called alignment constraints, i.e., wind turbines must be located at the intersections of a parallelogram-made grid. The shape and orientation of these parallelograms are to be optimally determined to minimize wake losses. **To the authors' best knowledge** and despite its practical interest, the wind farm layout optimization problem under alignment constraints has not been investigated in the literature. **The contributions of this paper are twofold, the first contribution is a dedicated optimization method to handle this problem, and the second contribution is to provide a challenging benchmark based on open data for layout optimization with alignment constraints.**

1 Introduction

10 Selecting a proper layout is an important task when building a wind farm. A layout far from optimal is prone to significant loss of expected Annual Energy Production (AEP) due to wake effects within the farm. Having an optimized method of turbine placement in a given area helps to maximize the energy production over the life span of the wind farm. In its full generality, the problem of optimizing a wind farm layout is a complex one for several reasons. The first is that **computing a given farm's mean annual energy production is numerically complex**, i.e., evaluating the optimization problem's objective function is computationally time-consuming. The second difficulty is that the problem is not convex, i.e., neither the objective function nor the minimization set are convex. As a result, the problem of wind farm layout optimization requires developing dedicated optimization tools. Wind farm optimization has been the subject of much scientific research, see for example, Herbert-Acero et al. (2014) for a review of such methods. Let us now focus on recent contributions to the field. In Quick et al. (2023), the authors develop a stochastic gradient-based method for wind farm optimization. The presented algorithm is developed for circular or square domains and could be easily extended to convex domains but not to non-convex or non-connected ones. In Kumar and Sharma (2023), the authors use a so-called teaching-learning-based algorithm to also solve the wind farm layout optimization problem for a circular domain. In Liang and Liu (2023), the authors use genetics and particle swarm algorithms to solve the problem on a square domain. In Fischetti and Fischetti (2022), the authors propose a Mixed Integer Linear Programming model to solve turbine placement and cable routing optimization problems. In Kunakote et al. (2022), the authors compare 12 meta-heuristic methods for wind farm layout optimization. The presented methods do not rely on

provide ref to the claim



any assumption on the shape of the admissible domain. However, the method relies on a very coarse discretization of the domain and can be numerically intractable using a finer one. In Thomas et al. (2023), the authors compare eight wind farm optimization methods and provide a benchmark case study for comparing algorithm performances. The proposed benchmark is highly complex since the admissible domain is neither convex nor connected. However, no alignment constraints are taken into account in this contribution. Finally, in Stanley and Ning (2019), the authors propose a so-called inner-grid wind farm layout parameterization that satisfies strong alignment constraints. However, the authors assume a one-to-one correspondence between this parameterization and the layout configuration, dramatically reducing the degree of freedom and potentially leading to far-from-optimal solutions. In fact, despite the extensive literature on wind farm optimization, to the best of our knowledge, no other method than the latter can handle turbine alignment constraints. By alignment constraint, we mean that we place the turbines on the intersections of a regular grid made of parallelograms whose shape and orientation are to be determined. Far from being just an academic question, turbine alignment constraints are, in practice, often imposed on developers by maritime authorities to secure the navigation of boats within the wind farm. The contribution of this paper is to provide an optimization algorithm for wind farm layout optimization that is able to handle alignment constraints. Mathematically, these alignment constraints make the wind farm layout optimization problem a mixed integer non-linear programming (MINLP). The integer variables are the positions of the turbines, which belong to the finite set of grid intersections located in the admissible domain. The continuous variables are the grid parameters, that is to say the size and orientation of the grid's unit parallelogram. The non-linearity mainly stems from the wind farm's Annual Energy Production (AEP) as a function of the optimization parameters. These problems are generally extremely difficult to solve. As detailed in Burer and Letchford (2012), solving algorithms for non-convex MINLP falls into two different categories: exact methods and heuristics-based methods. Exact methods often rely on Branch and Bound methods Papadimitriou and Steiglitz (1998) or separation properties of the objective function. Heuristics methods include tabu search Exler et al. (2008), particle swarm algorithms Yiqing et al. (2007); Young et al. (2007), genetic algorithms Schlüter et al. (2009) or local search methods Liberti et al. (2011). The strategy adopted in this paper is to adapt the DEBO method the authors developed in Thomas et al. (2023) to the problem at hand. This method is a local-search-based method coupled with an optimization-parameters-set exploration heuristic. The paper is organized as follows. In section 2, we introduce useful notations and definitions. In section 3, we describe the aligned-layout optimization problem; that is to say, we present the objective function, the constraints, and the optimization variables. We fully describe the optimization algorithm in section 4. In section 5, we take up the benchmark presented in Thomas et al. (2023) and add the alignment constraints, and we conduct a thorough study on the setting of the optimization algorithm hyper-parameters. In section 6, we illustrate the impact of the alignment-grid parameters exploration method on the AEP and prove that an efficient exploration method yields a strong improvement of the AEP. Finally, in section 7, we give the conclusions of this work and draw up research perspectives on the subject.

2 Notations and definitions

Throughout the paper we will use recurrently the following notations



- \mathbb{R}, \mathbb{R}_+ denote respectively the set of real numbers and the set of non negative real numbers.
- \mathbb{Z}, \mathbb{Z}_* denote respectively the set of integers and the set of non zero integers
- $\Omega \in \mathbb{R}^2$: Two dimensional domain where turbines can be planted
- N_{\max} : Maximal number of turbines to be placed within the admissible domain E
- $\text{turb}_{\text{diam}}$: Turbine diameter
- D_{\min} : Minimal distance between turbines
- D_{\max} : Maximal distance between turbines
- w_s : Wind speed
- w_d : Wind direction
- \top : Logical True
- \perp : Logical False
- \neg : Logical negation
- \wedge : Logical conjunction (and)
- \vee : Logical disjunction (or)

Definition 1 (Wind farm). A capital bold character associated with a subscript such as \mathbf{F}_n denotes a n -turbines wind farm. Mathematically \mathbf{F}_n is a function satisfying:

$$75 \quad \mathbf{F}_n : \{1, \dots, n\} \ni k \mapsto (x_k \ y_k)^\top \in \mathbb{R}^2 \quad (1)$$

where $(x_k \ y_k)^\top$ is the position of the k^{th} -turbine. Let \mathbf{F}_n and let $(x \ y)^\top \in \mathbb{R}^2$, we denote $\mathbf{H}_{n+1} := \mathbf{F}_n \oplus (x \ y)$ the wind farm defined as follows

$$\mathbf{H}_{n+1}(k) := \begin{cases} \mathbf{F}_n(k) & \text{if } k \leq n \\ (x \ y)^\top & \text{if } k = n + 1 \end{cases} \quad (2)$$

Definition 2 (Wind farm Power Production). We denote $\mathcal{P} : (\mathbf{F}_n, w_s, w_d) \mapsto \mathbb{R}_+$ the power production of the wind farm \mathbf{F}_n for a wind speed w_s and a wind direction w_d .

Definition 3 (Wind random variable). Let (E, \mathbb{P}) be a probability space. We denote $W : E \mapsto Z := \mathbb{R}^+ \times [0, 2\pi)$ the wind random variable which associates a random event, denoted $e \in E$, to a wind configuration $(w_s \ w_d) \in Z$, that is to say, $W(e) =$



(w_s, w_d) . We also denote \mathbb{P}_W the probability measure on Z associated with the random variable W . Finally, we denote \mathbb{E}_W the expectation with respect to the probability \mathbb{P}_W defined as

$$85 \quad \mathbb{E}_W(f) := \int_Z f(w_s, w_d) d\mathbb{P}_W(w_s, w_d) \quad (3)$$

for all measurable function $f : Z \mapsto \mathbb{R}$.

3 Optimization model for layout optimization with alignment constraints

The optimization problem we are interested in consists of optimizing the grid configuration and the turbine placement on the intersections of this grid. This optimization problem is a non-linear mixed integer programming problem, a class of problems
 90 known to be challenging to solve. In this section, we describe the parameterization of our problem.

3.1 Grid parameterization

To write the optimization problem, we parameterize the grid using 6 parameters $(r_1, r_2, \theta_1, \theta_2, v_x, v_y)$ as represented on fig. 1. Using this parameterization we define the change-of-basis matrix from the canonical basis denoted \mathcal{B}_0 to the grid basis denoted $\mathcal{B}(\theta_1, \theta_2, r_1, r_2)$ as follows

$$95 \quad P_{\mathcal{B}_0}^{\mathcal{B}(\theta_1, \theta_2, r_1, r_2)} = \begin{pmatrix} r_1 \cos(\theta_1) & r_2 \cos(\theta_2) \\ r_1 \sin(\theta_1) & r_2 \sin(\theta_2) \end{pmatrix} \quad (4)$$

In the grid-basis coordinates, any intersection point p writes as follows:

$$p := \begin{pmatrix} k_1 \\ k_2 \end{pmatrix} + \left(P_{\mathcal{B}_0}^{\mathcal{B}(\theta_1, \theta_2, r_1, r_2)} \right)^{-1} \begin{pmatrix} v_x \\ v_y \end{pmatrix} \quad k_1, k_2 \in \mathbb{Z}$$

This parameterization in grid basis is, in turn, equivalent to

$$p = \begin{pmatrix} k_1 \\ k_2 \end{pmatrix} + \begin{pmatrix} \Delta_1 \\ \Delta_2 \end{pmatrix} \quad k_1, k_2 \in \mathbb{Z} \text{ and } \Delta_1, \Delta_2 \in [0, 1) \quad (5)$$

100 3.2 Layout parameterization

Using the grid parameterization described in section 3.1, an aligned layout has its turbines located on the intersections of the grid which writes

$$\mathbf{F}[\mathcal{B}]_n(i) : \{1, \dots, n\} \ni i \mapsto \begin{pmatrix} k_1^i & k_2^i \end{pmatrix}^\top + \begin{pmatrix} \Delta_1 & \Delta_2 \end{pmatrix}^\top, \quad k_1^i, k_2^i \in \mathbb{Z}; \quad \Delta_1, \Delta_2 \in [0, 1) \quad (6)$$

The corresponding wind farm in canonical coordinates \mathbf{F}_n thus writes

$$105 \quad \mathbf{F}_n(i) = P_{\mathcal{B}_0}^{\mathcal{B}(\theta_1, \theta_2, r_1, r_2)} \mathbf{F}[\mathcal{B}]_n(i), \quad i = 1, \dots, n \quad (7)$$

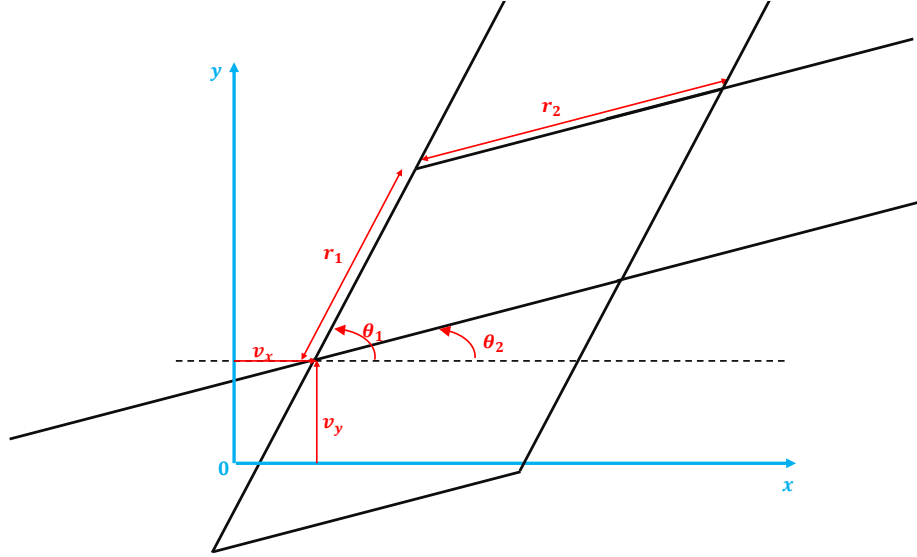


Figure 1. Grid parameterization for aligned layout

3.3 Optimization problem

We are now ready to write the general wind farm layout optimization problem with alignment constraints. This optimization problem consists of maximizing the AEP, which, in turn, is equivalent to maximizing the expected power production of the wind farm with respect to the wind random variable as defined in eq. (3). This writes

$$110 \quad \max_{(k_1^i, k_2^i)_{i=1, \dots, N_{\max}}, \Delta_1, \Delta_2, r_1, r_2, \theta_1, \theta_2} \mathbb{E}_W [\mathcal{P}(\mathbf{F}[\mathcal{B}]_{N_{\max}}, w_s, w_d)] \quad (8)$$

under the following constraints

$$k_1^i, k_2^i \in \mathbb{Z}; \quad i = 1, \dots, N_{\max} \quad (9)$$

$$\left| k_1^i - k_1^j \right| + \left| k_2^i - k_2^j \right| \geq 1; \quad \forall i \neq j \quad (10)$$

$$\Delta_1, \Delta_2 \in [0, 1) \quad (11)$$

$$115 \quad \mathbf{F}_{N_{\max}}(i) \in \Omega; \quad i = 1, \dots, N_{\max} \quad (12)$$

$$\theta_1 \in \left(-\frac{\pi}{2}, \frac{\pi}{2} \right] \quad (13)$$

$$\theta_2 \in \left[-\frac{\pi}{2}, \theta_1 \right) \quad (14)$$

$$D_{\min} \leq \min_{z \in \mathbb{Z}_*^2} \left\| P_{B_0}^{\mathcal{B}(\theta_1, \theta_2, r_1, r_2)} z \right\| \quad (15)$$

Equations (9) to (11) ensure that the turbines are located at the intersections of the grid defined by the parameters

120 $(r_1, r_2, \theta_1, \theta_2, v_x, v_y)$ and thus, that the turbines are aligned along the directions θ_1 and θ_2 . The constraint from eq. (12) guar-



antees that the turbines are located in the admissible domain. Constraints defined in eqs. (13) and (14) allow to generate all possible parallelogram-based grids. Finally, the constraint from eq. (15) guarantees that the minimal distance between two turbines is greater than D_{\min} .

4 Solving Algorithm

125 4.1 General description of the proposed solving algorithm

The method presented in this paper belongs to the category of heuristic-based methods and consists in the following steps.

1. The first step consists of computing the set $R_{1,2}$ of parameters (r_1, r_2) by discretization of the space $[D_{\min}, D_{\max}]^2$ using a grid size of Δr .
- 130 2. The second step consists in reducing the size of the angle-search space. To do so, for each couple $(r_1, r_2) \in R_{1,2}$, we discretize the search space $(-\frac{\pi}{2}, \frac{\pi}{2}] \times [-\frac{\pi}{2}, \theta_1)$ using a discretization size of $\Delta\theta$. Then, for each grid configuration $(r_1, r_2, \theta_1^k, \theta_2^k)_k$ satisfying eq. (15) we compute the AEP of an elementary 4 turbines wind farm. Then, we store the N_θ best angle configurations (θ_1, θ_2) in a angle set Θ . This latter set Θ is the reduced angle-search space.
3. Then, we compute a set of grid configurations $(r_1, r_2, \theta_1, \theta_2)$ denoted grids defined as grids := $\{(r_1, r_2, \theta_1, \theta_2) : (r_1, r_2) \in R_{1,2}, (\theta_1, \theta_2) \in \Theta, \text{ eq. (15) holds}\}$
- 135 4. For each explored shape configuration $(r_1, r_2, \theta_1, \theta_2)$, compute an optimal layout using a greedy algorithm for placing the N_{\max} -turbines on the intersections of the grid and using a local search optimization method to move the turbines on the intersections. The sequence of greedy initialization followed by a local search method has already been proved efficient for wind farm layout optimization without alignment constraints, see the DEBO algorithm from Thomas et al. (2023).

140 4.2 Angle search space reduction and grid configuration selection

In this section, we describe the first part of the algorithm which consists in finding a set of grid configurations $(r_1, r_2, \theta_1, \theta_2)$ of reasonable size and to perform a complete wind farm layout optimization for each element of this set. To do so, we first compute the set $R_{1,2}$ of parameters (r_1, r_2) by discretizing the space $[D_{\min}, D_{\max}]^2$ using a discretization of size Δr . Then, for each $(r_1, r_2) \in R_{1,2}$, discretize the following search space

$$145 \quad S := \left\{ (\theta_1, \theta_2) \in \left[-\frac{\pi}{2}, \frac{\pi}{2}\right]^2 : \theta_1 \geq -\frac{\pi}{2} + \Delta\theta, \theta_2 \leq \theta_1 - \Delta\theta \right\} \quad (16)$$

with an angle discretization parameter $\Delta\theta$. We denote S_D this discrete search space. Then, for each $(r_1, r_2) \in R_{1,2}$, we define the corresponding angle search space Θ_{r_1, r_2} as follows

$$\Theta_{r_1, r_2} := \{(\theta_1, \theta_2) \in S_D : \text{eq. (15) holds}\} \quad (17)$$

Then, for each configuration $(r_1, r_2, \theta_1^k, \theta_2^k)_k$ with $(\theta_1^k, \theta_2^k) \in \Theta_{r_1, r_2}$ we compute the AEP of the elementary farms $(\mathbf{F}[\mathcal{B}(r_1, r_2, \theta_1^k, \theta_2^k)]_4)_k$

150 defined as follows

$$\mathbf{F}[\mathcal{B}(r_1, r_2, \theta_1^k, \theta_2^k)]_4(i) := \begin{cases} (0 \ 0)^\top & \text{if } i = 1 \\ (1 \ 0)^\top & \text{if } i = 2 \\ (0 \ 1)^\top & \text{if } i = 3 \\ (1 \ 1)^\top & \text{if } i = 4 \end{cases} \quad (18)$$

and sort the couples $(\theta_1^k, \theta_2^k)_i$ by decreasing order of AEP. Finally, for each $(r_1, r_2) \in R_{1,2}$, we store in the set Θ the best N_θ angles configuration $(\theta_1^k, \theta_2^k) \in \Theta_{r_1, r_2}$. Then, the continuous variables search-space denoted grids consists in all the combinations of the $(r_1, r_2) \in R_{1,2}$ explored with all the angles configuration from Θ , i.e.

$$155 \text{ grids} := \{(r_1, r_2, \theta_1, \theta_2) : (r_1, r_2) \in R_{1,2}, (\theta_1, \theta_2) \in \Theta : eq. (15) \text{ holds}\} \quad (19)$$

The corresponding algorithm in pseudo-code is described in algorithm A1, algorithm A2, algorithm A3, algorithm A4.

4.3 Compute intersections for each grid configuration

This part of the algorithm consists of traversing $\text{grids}(k)$ and, for each configuration $(r_1^k, r_2^k, \theta_1^k, \theta_2^k)$, calculating the maximum number of intersections located in the admissible domain Ω and their positions. If this set of intersections has more than N_{\max} elements and if all intersections are D_{\min} -apart from each other, this set of intersections is stored in a set of set-of-intersections that we denote $\text{intersections_sets}$. The corresponding algorithm is written in pseudo-code in algorithm A5.

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4.4 Optimize turbines placement

4.4.1 Greedy Initialization

Given a grid configuration $(r_1, r_2, \theta_1, \theta_2, \Delta_1, \Delta_2)$, a greedy algorithm is used to sequentially place N_{\max} turbines on the admissible intersections. This algorithm consists in sequentially placing the turbines on the best possible empty intersection, in the sense of AEP maximization, until N_{\max} turbines are placed. The corresponding algorithm in pseudo-code is given in algorithm A6.

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4.4.2 Local Search

This part of the algorithm sequentially moves each turbine in random order from its current intersection to a free one if it provides a strict increase in AEP. The algorithm stops when a complete course of all the turbines has been made without a single one being moved. When the number of intersections in the admissible domain is much bigger than N_{\max} , one can explore a subset of the free intersections. For example, one can explore the p closest intersections from the turbine to be moved or select p random free intersections. In this case, the size of the subset to explore and its definition, p , are user-defined parameters. The algorithm in pseudo-code is given in algorithm A7.

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175 4.4.3 Turbine placement optimization

Finally, given a set of intersections, the optimization algorithm for optimal turbine placement consists of using sequentially the greedy initialization and the local search algorithm as described in pseudo-code in algorithm A9.

4.5 Complete Algorithm

180 Finally, the complete algorithm includes all the blocks described in sections 4.3 and 4.4. The corresponding pseudo-code is displayed in algorithm A10. As one can see on lines 2, and 6 from algorithm A10, large parts of the proposed algorithm can be run in parallel.

5 Numerical Examples

5.1 Problem presentation

how does your compare with the DEBO algorithm?

185 For this numerical example, we use the same case study as in Thomas et al. (2023), whose data are available in Baker et al. (2021). This case study was created within the International Energy Association (IEA) Wind Task 37, and is based on the Borssele III and IV wind farms. Of particular interest in this case study is the presence of five disconnected boundary regions and concave boundary features, as shown in fig. 2. The turbines are 10 MW machines with 198 m rotor diameters based on the IEA 10 MW reference wind turbine (Bortolotti et al. (2019)). For the AEP computation, we also use the same algorithm as in Thomas et al. (2023). This method is based on a simple Gaussian wake model based on Bastankhah's Gaussian wake model (Bastankhah and Porté-Agel (2016)), and presented in the IEA case study 3 and 4 announcement documents (Baker et al. (2021)), to calculate wind speeds at each turbine in the wind farm. However, any other AEP computation software, such as FLORIS, can be used with the presented algorithm as long as the computation time of the AEP is fast enough. Indeed, our optimization algorithm requires a large number of AEP evaluations.

5.2 Influence of the hyper-parameters on the AEP and the computation time

195 The optimization procedure described in section 4 requires setting 5 hyper-parameters D_{\min} , D_{\max} , $\Delta\theta$, N_θ , and Δr . The turbine's manufacturer usually sets D_{\min} at a fixed value. In this example, we set $D_{\min} = 2\text{turb}_{\text{diam}}$. The parameter D_{\max} must be chosen large enough to allow a good exploration range for the grid parameters (r_1, r_2) . However, setting D_{\max} with a significant value generates grids with a number of admissible intersections smaller than the number of turbines to be placed, i.e., in generating non-admissible layouts. Therefore, we have set $D_{\max} = 6\text{turb}_{\text{diam}}$. The parameter $\Delta\theta$ should be chosen to the minimal value such that the wake model used to compute the AEP is valid. For this example, we set $\Delta\theta = 1^\circ$. The remaining hyper-parameters, N_θ , and Δr , dramatically affect the optimization procedure regarding AEP value and computation time. Indeed, as explained in section 4.2, the larger N_θ , the larger the reduced angle-set denoted Θ , and the smaller Δr , the larger the set $R_{1,2}$. The number of configurations to optimize being the product of the cardinal of the sets Θ and $R_{1,2}$, the larger these sets, the longer the computation time. However, the more configuration to optimize, the greater the AEP. Therefore,

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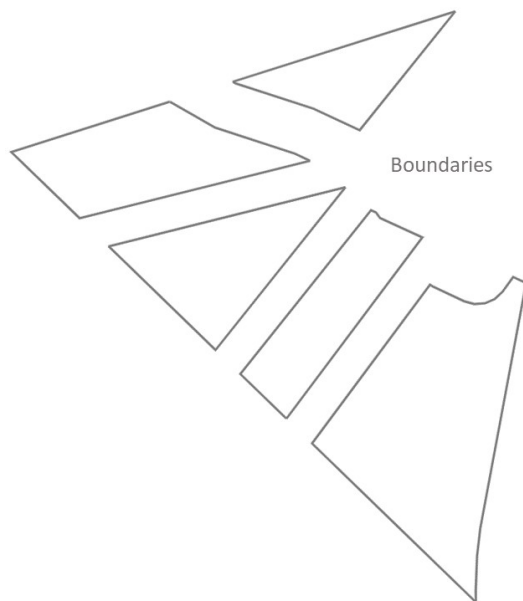


Figure 2. An overhead view of the boundaries of the admissible domain Ω

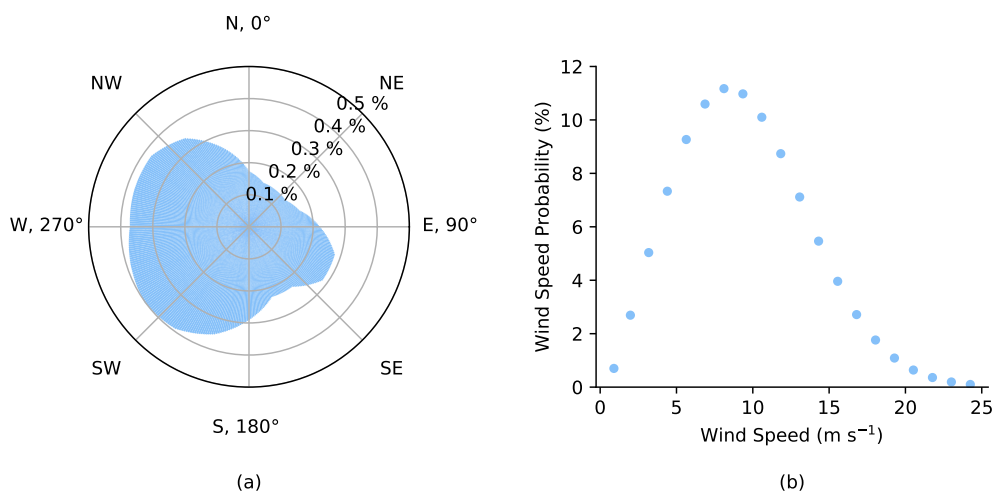


Figure 3. This figure, reproduced from Thomas et al. (2023), displays the full wind resource used for evaluating the final wind farm layouts. (a) The wind direction probability (360 bins). (b) A representative wind speed probability distribution (20 bins).

205 any layout optimization needs to make a trade-off between computation time and size of the set of configuration to optimize. In this section, we will show the effect of the parameters N_θ and Δr on the optimal AEP and the computation time, and give the user some guidelines to set these parameters. To do so, we run algorithm A10 for all possible configurations of the



hyper-parameters valued in their respective value-set given in table 1, for wind farm sizes of 81, 100, 150, and 250 turbines respectively. The numerical results of these optimizations are gathered in table 2 and illustrated in figs. 4 and 5. On fig. 4,

D_{\min}	D_{\max}	$\Delta\theta$	N_θ	Δr
$\{2 \text{ turb}_{\text{diam}}\}$	$\{6 \text{ turb}_{\text{diam}}\}$	$\{1^\circ\}$	$\{1, 5, 10\}$	$\left\{\frac{\text{turb}_{\text{diam}}}{2}, \text{turb}_{\text{diam}}, 2 \text{ turb}_{\text{diam}}\right\}$

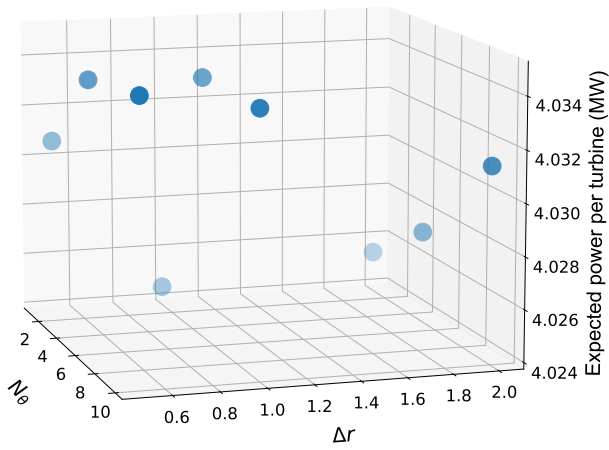
Table 1. Value set of each hyper-parameter

210 one can see that the expected power per turbine¹ is growing with respect to N_θ and decreasing with respect to Δr . Also, when $N_\theta \geq 5$ and $\Delta r \leq 1 \text{ turb}_{\text{diam}}$, the expected powers per turbine are similar whatever the value of these hyper parameters. However, as illustrated on fig. 5, the execution time is strongly increasing with respect to N_θ and strongly decreasing with respect to Δr . Therefore, if algorithm A10 is run using an AEP computation method more precise and computationally more expensive than the one we used, (see Baker et al. (2021); Thomas et al. (2023)), keeping N_θ reasonably small (≈ 5) and Δr 215 reasonably large (≈ 1) should enable the solving algorithm to find a well-performing layout in a reasonable execution time. In addition, as illustrated in table 1, the solving algorithm often sets the optimal shape parameters (r_1, r_2) to their minimal authorized values. This behavior indicates that the method generates grids with many intersections and, thus, a large degree of freedom for the local search part of the algorithm. The larger the degree of freedom for the local-search algorithm, the better the solution. The best layout for each wind farm size is displayed on fig. 6 and the optimal parameters $(r_1, r_2, \theta_1, \theta_2)$, the optimal 220 AEP, the optimal expected power per turbine, and the execution time are displayed on table 3.

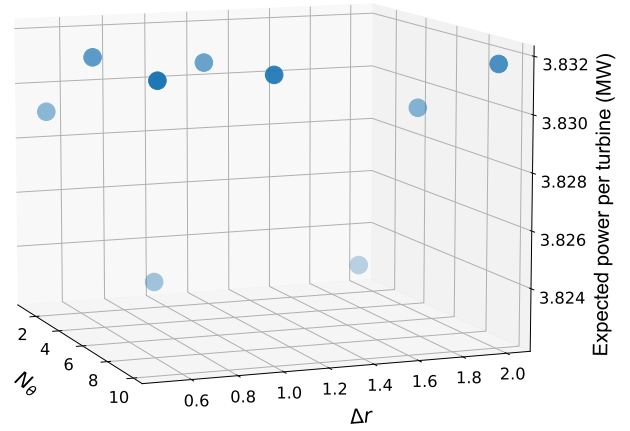
6 Exploration method's impact on the AEP

The optimization layout algorithm presented in this paper relies on the discrete exploration of the space of shape parameters $(r_1, r_2, \theta_1, \theta_2) \in [D_{\min}, D_{\max}]^2 \times [-\pi/2, \pi/2]^2$. Despite the angles' search-space reduction technique presented in section 4.2 and algorithm A2, exploring this space using fine discretization is numerically too demanding. Unfortunately, the performance 225 of the optimization depends on the size of the discretization step; the smaller this size, the higher the AEP. Therefore, there is a strong incentive to develop heuristic methods to explore the shape parameters space other than by using the angle search space reduction associated with a brute force-like exploration method. In this section, we present optimization results using such a heuristic to provide a benchmark for an aligned optimization algorithm. Unfortunately, for industrial confidentiality reasons, we do not describe its principle and only focus on the improvement in terms of AEP. Again, we have run the optimization 230 procedure for wind farms of 81, 100, 150, and 250 turbines. The results in terms of optimal shape parameters, AEP, expected power per turbine, and wake losses are summarized in table 4, and the optimal layouts are displayed in fig. 7. The optimal layout obtained using this heuristic exhibits the same behavior as those found in the previous section in terms of r_1 and r_2 . Indeed, these parameters are systemically found to be equal to the lowest possible value. On the contrary, the optimal angles are not the same. One of the alignment directions is conserved ($\approx 18^\circ$), but the other one is quite different even when taking

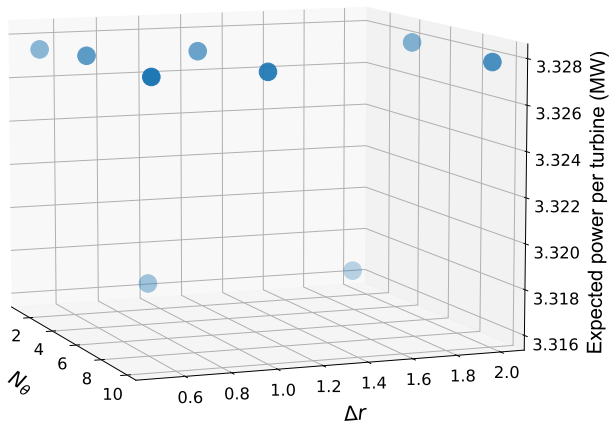
¹For a N_t -turbines wind farm, the expected power per turbine is given by the formula $\text{AEP}(\text{MWh}) / (8760 \times N_t)$ and allows for comparing wind farms of different sizes.



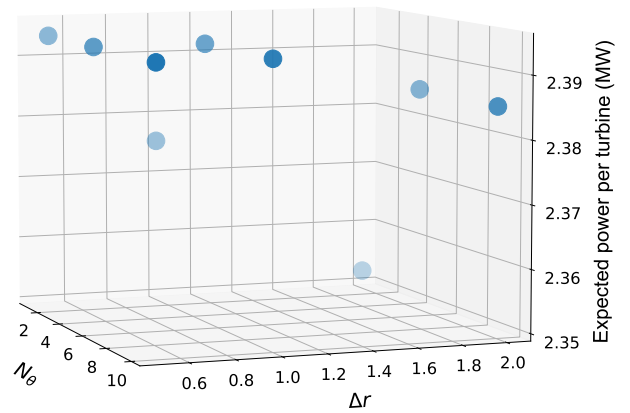
(a) Expected power per turbines for a 81-turbines wind farm as a function of N_θ and Δr



(b) Expected power per turbines for a 100-turbines wind farm as a function of N_θ and Δr

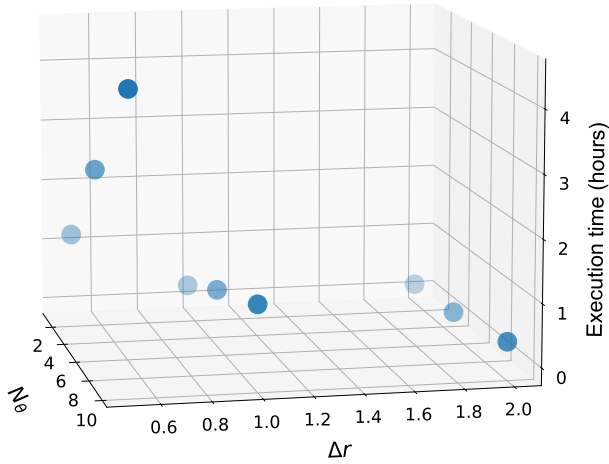


(c) Expected power per turbines for a 150-turbines wind farm as a function of N_θ and Δr

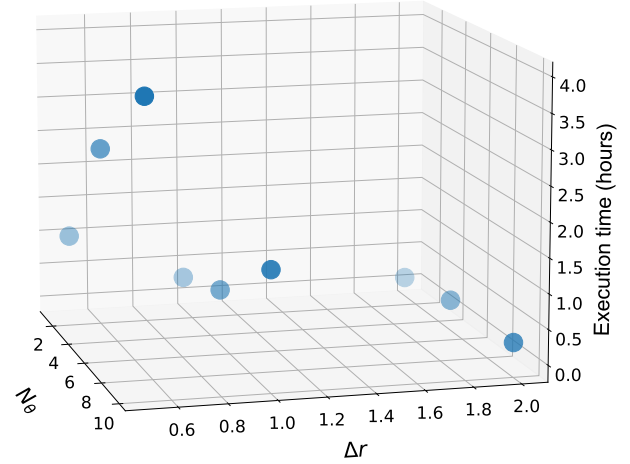


(d) Expected power per turbines for a 250-turbines wind farm as a function of N_θ and Δr

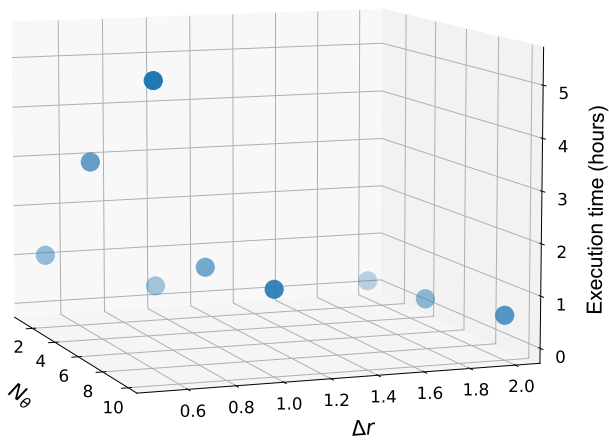
Figure 4. Expected power per turbine for 81, 100, 150, and 250 turbines wind farms as a function of the hyper-parameters N_θ , and Δr .



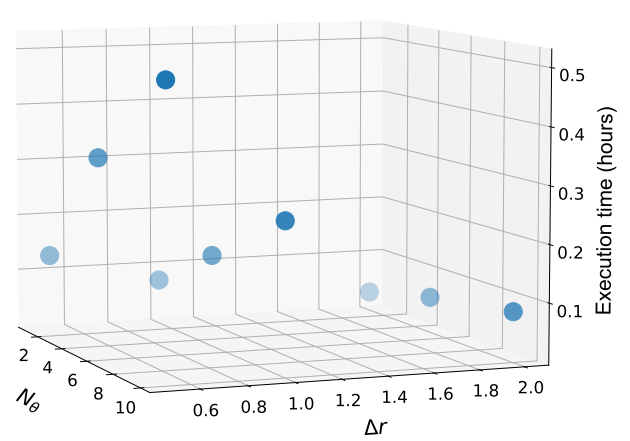
(a) Execution time of algorithm A10 as a function of the hyper-parameters N_θ , Δr for a 81-turbines wind farm



(b) Execution time of algorithm A10 as a function of the hyper-parameters N_θ , Δr for a 100-turbines wind farm

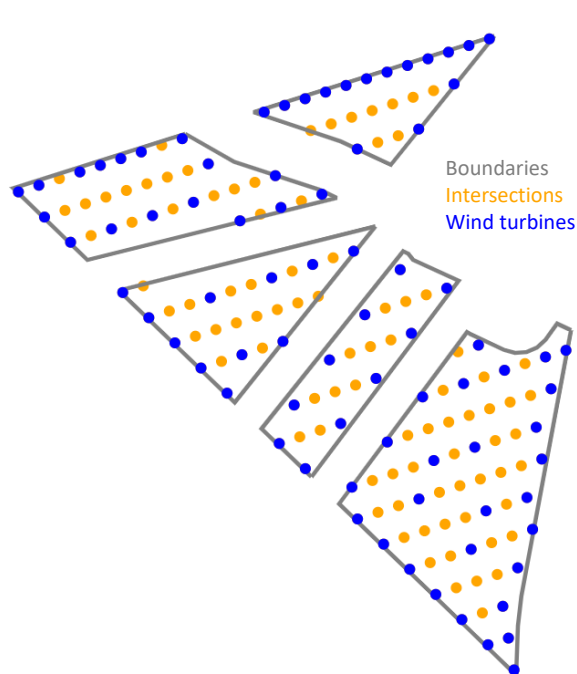


(c) Execution time of algorithm A10 as a function of the hyper-parameters N_θ , Δr for a 150-turbines wind farm

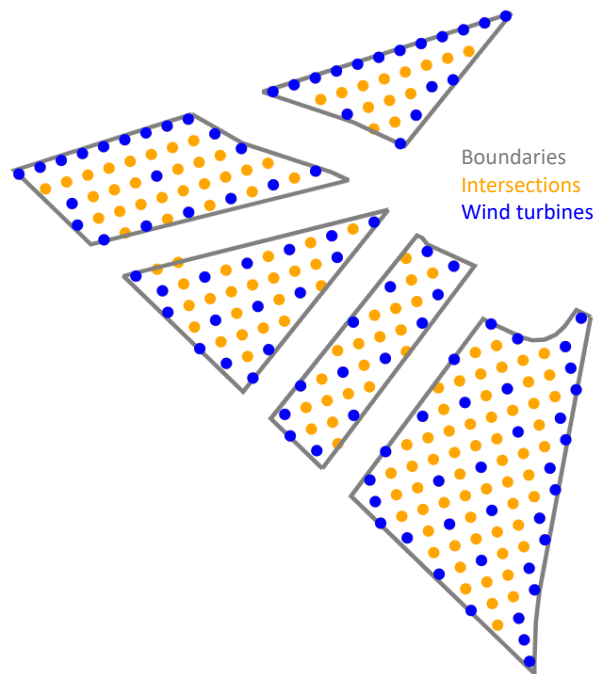


(d) Execution time of algorithm A10 as a function of the hyper-parameters N_θ , Δr for a 250-turbines wind farm

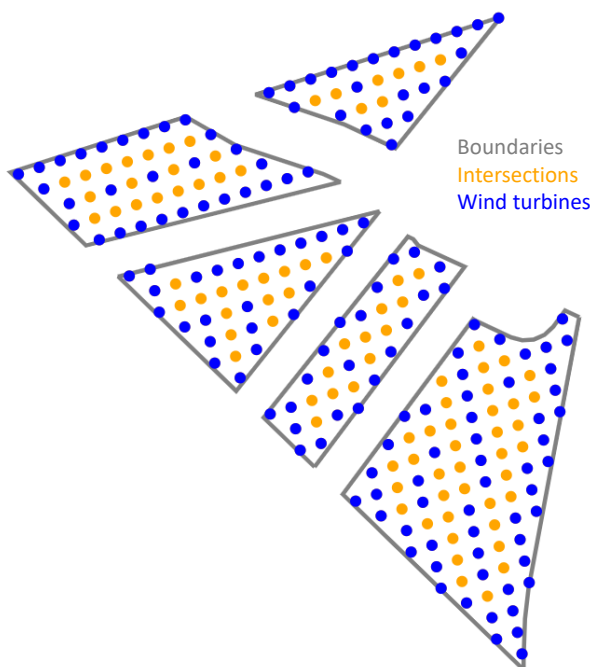
Figure 5. Execution time of algorithm A10 for 81, 100, 150, and 250 turbines wind farms as a function of the hyper-parameters N_θ , and Δr . All optimizations were run on a 12th Gen Intel(R) i7-12700H 2.30 GHz core.



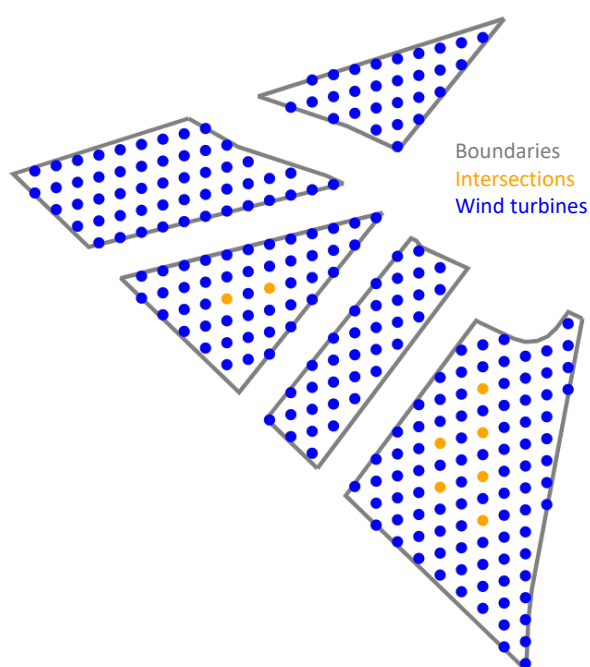
(a) Best 81-turbines wind farm layout



(b) Best 100-turbines wind farm layout



(c) Best 150-turbines wind farm layout



(d) Best 250-turbines wind farm layout

Figure 6. Best layouts for wind farm sizes of 81, 100, 150, 250 turbines using algorithm A10.



235 into account the 180° periodicity of the angles. Concerning the AEP, using a heuristic to explore the space of shape parameters
more efficiently allows for improvement. Interestingly, the percentage of AEP increase grows almost linearly concerning the
wind farm size and reaches 1% for the larger one. This behavior stems from the decreasing degrees of freedom in the turbine's
optimal placing problem as the wind farm size grows. Therefore, for larger farms, the efficiency of the shape parameters
optimization algorithm is of greater importance than for smaller farms; thus, there is a more substantial improvement of AEP
240 for large farms when using a better exploration algorithm for the space of shape parameters. These results prove a strong
interest in developing efficient heuristics to explore the space of shape parameters.

7 Conclusions

This work tackles the wind farm layout optimization problem with alignment constraints. We introduced a model of the corre-
sponding optimization problem and adapted the DEBO algorithm from Thomas et al. (2023) to this new problem. The proposed
245 method is based on an exploration heuristic for computing the grid parameters and a local-search method to place the turbines
on the grid's intersections optimally. **Can this statement be quantified, and be explicitly defined in previous section by way of comparison**
We have shown that this method performs well on the benchmark of IEA Wind task 37
(Thomas (2022)) by outperforming the initial layout, even though the latter does not satisfy any alignment constraints and
is potentially less prone to significant wake losses. Using this numerical example, we have also demonstrated the benefits of
developing efficient heuristics for exploring the grid parameters. Indeed, using efficient heuristics allows for a better trade-
250 off between wake-losses reduction and computation time. Therefore, these heuristics can be used to find layouts with higher
AEP or to use more precise and computationally demanding AEP models. Finally, a more efficient algorithm can enable the
introduction of other optimization parameters or constraints, such as cable routing or shared mooring for floating farms.

Data availability. Provided physics model, turbines and boundary data are available at Thomas (2022), optimal layouts, AEPs, shape con-
figurations, and intersections are available at Malisani (2024)

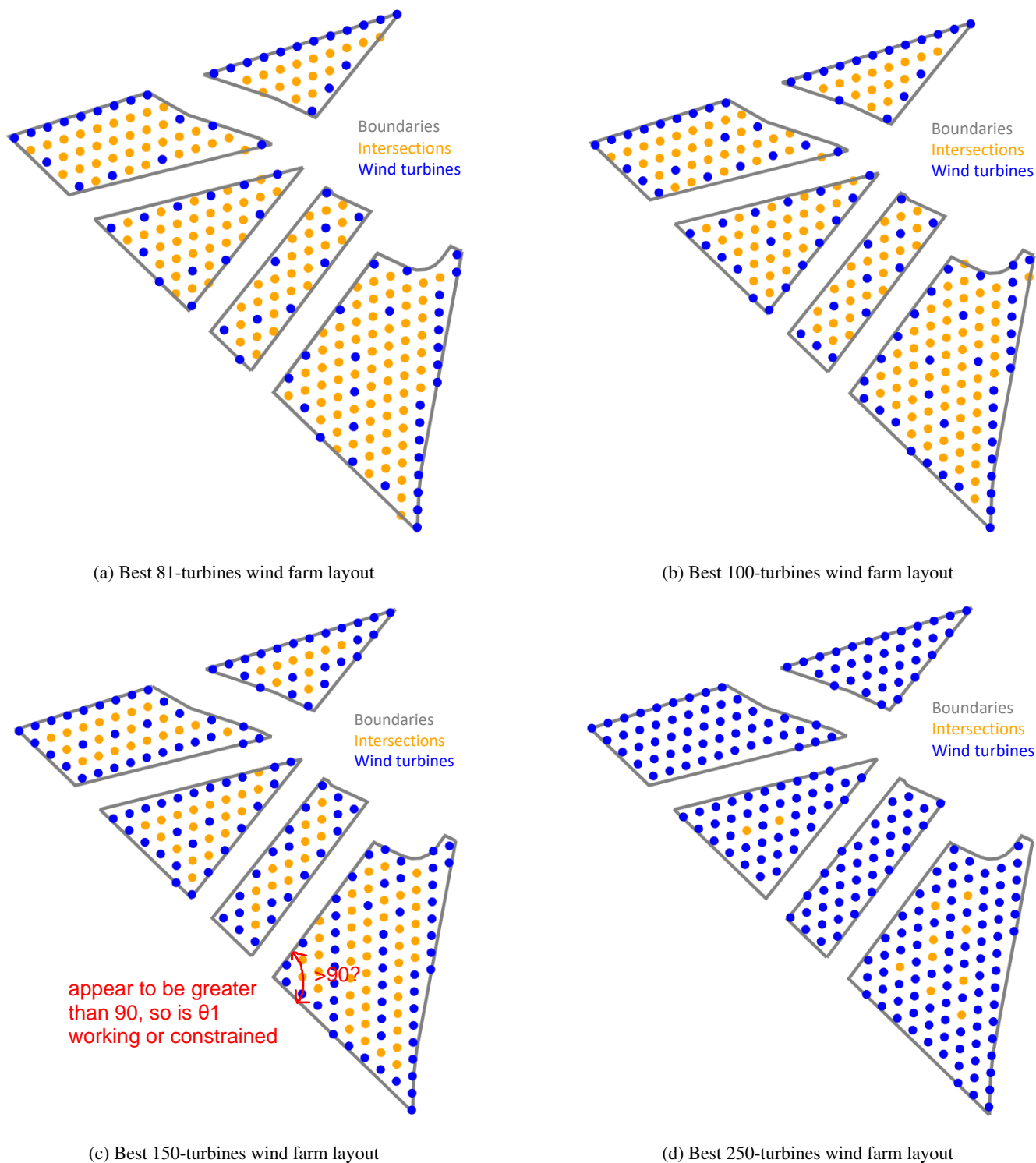


Figure 7. Best layouts for wind farm sizes of 81, 100, 150, 250 turbines using an efficient shape parameters exploration method and the same local-search algorithm.



Wind farm size	Δr	N_θ	$(r_1, r_2, \theta_1, \theta_2)$	AEP (GWh)	Expected power per turbine (MW)	Exec. time (s)
81	0.5	1	(5.5 turb _{diam} , 2 turb _{diam} , 73°, -87°)	2860.00	4.031	4083
81	0.5	5	(2 turb _{diam} , 3 turb _{diam} , 18°, -80°)	2862.37	4.034	9611
81	0.5	10	(2 turb _{diam} , 3 turb _{diam} , 18°, -80°)	2862.76	4.035	15 981
81	1	1	(2 turb _{diam} , 6 turb _{diam} , 90°, 70°)	2855.62	4.024	690
81	1	5	(2 turb _{diam} , 3 turb _{diam} , 18°, -80°)	2862.29	4.034	2343
81	1	10	(2 turb _{diam} , 3 turb _{diam} , 18°, -80°)	2862.29	4.034	3944
81	2	1	(2 turb _{diam} , 6 turb _{diam} , 90°, 70°)	2856.23	4.025	161
81	2	5	(2 turb _{diam} , 2 turb _{diam} , 18°, -78°)	2857.65	4.027	399
81	2	10	(2 turb _{diam} , 2 turb _{diam} , 18°, -76°)	2860.44	4.031	1211
100	0.5	1	(2 turb _{diam} , 2 turb _{diam} , 18°, -78°)	3354.24	3.829	3486
100	0.5	5	(2 turb _{diam} , 2 turb _{diam} , 18°, -76°)	3356.53	3.832	9693
100	0.5	10	(2 turb _{diam} , 2 turb _{diam} , 18°, -76°)	3356.55	3.832	14105
100	1	1	(2 turb _{diam} , 2 turb _{diam} , 19°, -78°)	3348.50	3.822	884
100	1	5	(2 turb _{diam} , 2 turb _{diam} , 18°, -82°)	3356.21	3.831	2027
100	1	10	(2 turb _{diam} , 2 turb _{diam} , 18°, -76°)	3356.55	3.832	5324
100	2	1	(2 turb _{diam} , 2 turb _{diam} , 19°, -78°)	3348.57	3.823	158
100	2	5	(2 turb _{diam} , 2 turb _{diam} , 18°, -78°)	3354.45	3.829	746
100	2	10	(2 turb _{diam} , 2 turb _{diam} , 18°, -76°)	3356.54	3.832	920
150	0.5	1	(2 turb _{diam} , 2 turb _{diam} , 18°, -78°)	4372.17	3.327	3729
150	0.5	5	(2 turb _{diam} , 2 turb _{diam} , 18°, -78°)	4372.71	3.328	12013
150	0.5	10	(2 turb _{diam} , 2 turb _{diam} , 18°, -78°)	4372.71	3.328	19188
150	1	1	(2 turb _{diam} , 2 turb _{diam} , 19°, -78°)	4357.54	3.316	966
150	1	5	(2 turb _{diam} , 2 turb _{diam} , 18°, -78°)	4372.71	3.328	4151
150	1	10	(2 turb _{diam} , 2 turb _{diam} , 18°, -78°)	4372.71	3.328	4902
150	2	1	(2 turb _{diam} , 2 turb _{diam} , 19°, -78°)	4357.48	3.316	339
150	2	5	(2 turb _{diam} , 2 turb _{diam} , 18°, -78°)	4372.71	3.328	858
150	2	10	(2 turb _{diam} , 2 turb _{diam} , 18°, -78°)	4372.71	3.328	2084
250	0.5	1	(2 turb _{diam} , 2 turb _{diam} , 90°, 14°)	5241.50	2.393	462
250	0.5	5	(2 turb _{diam} , 2 turb _{diam} , 90°, 14°)	5241.50	2.393	1203
250	0.5	10	(2 turb _{diam} , 2 turb _{diam} , 90°, 14°)	5241.50	2.393	1789
250	1	1	(2 turb _{diam} , 2 turb _{diam} , 90°, 27°)	5202.29	2.375	262
250	1	5	(2 turb _{diam} , 2 turb _{diam} , 90°, 14°)	5241.50	2.393	555
250	1	10	(2 turb _{diam} , 2 turb _{diam} , 90°, 14°)	5241.50	2.393	925
250	2	1	(2 turb _{diam} , 2 turb _{diam} , 90°, 19°)	5150.62	2.352	100
250	2	5	(2 turb _{diam} , 2 turb _{diam} , 90°, 18°)	5223.08	2.385	205
250	2	10	(2 turb _{diam} , 2 turb _{diam} , 90°, 18°)	5223.08	2.385	293

Table 2. Influence of the hyper-parameters N_θ and Δr on the AEP and algorithm A10 execution time.



Number of turbines	AEP (GW h)	Shape parameters ($r_1, r_2, \theta_1, \theta_2$)	Expected power / turbine	% wake losses
1	42.55	—	4.86 MW	0
81	2862.76	(2 $\text{turb}_{\text{diam}}$, 3 $\text{turb}_{\text{diam}}$, 18° , -80°)	4.03 MW	17.1%
100	3356.55	(2 $\text{turb}_{\text{diam}}$, 2 $\text{turb}_{\text{diam}}$, 18° , -76°)	3.83 MW	21.2%
150	4372.71	(2 $\text{turb}_{\text{diam}}$, 2 $\text{turb}_{\text{diam}}$, 18° , -78°)	3.33 MW	31.5%
250	5241.50	(2 $\text{turb}_{\text{diam}}$, 2 $\text{turb}_{\text{diam}}$, 90° , 14°)	2.39 MW	50.8%

Table 3. Optimal AEP, shape configuration and mean power per turbine for an increasing number of turbines.

Number of turbines	AEP (GW h)	Shape parameters ($r_1, r_2, \theta_1, \theta_2$)	Expected power per turbine	% wake losses	% AEP increase w.r.t. table 2
1	42.550	—	4.86 MW	0	0
81	2866.697	(2 $\text{turb}_{\text{diam}}$, 2 $\text{turb}_{\text{diam}}$, 88.6° , 17.9°)	4.04 MW	16.8%	0.14 %
100	3369.709	(2 $\text{turb}_{\text{diam}}$, 2 $\text{turb}_{\text{diam}}$, 88.5° , 17.9°)	3.85 MW	20.8%	0.39 %
150	4399.174	(2 $\text{turb}_{\text{diam}}$, 2 $\text{turb}_{\text{diam}}$, 88.8° , 17.78°)	3.35 MW	31.1%	0.61 %
250	5308.184	(2 $\text{turb}_{\text{diam}}$, 2 $\text{turb}_{\text{diam}}$, 87.0° , 17.4°)	2.42 MW	50.1%	1.27 %

Table 4. Optimal AEP, shape configuration and mean power per turbine for an increasing number of turbines using a fast heuristic for the optimization of the shape's parameters



255 Appendix A: Algorithms in pseudo-code

Algorithm A1 GenerateR1R2($\Delta r, D_{\min}, D_{\max}$)

```
1:  $R_{1,2} \leftarrow \emptyset$ 
2:  $r_1 \leftarrow D_{\min} \cdot \text{turb}_{\text{diam}}$ 
3:  $\text{angles} \leftarrow \emptyset$ 
4: while  $r_1 \leq D_{\max} \cdot \text{turb}_{\text{diam}}$  do
5:    $r_2 \leftarrow D_{\min} \cdot \text{turb}_{\text{diam}}$ 
6:   while  $r_2 \leq D_{\max} \cdot \text{turb}_{\text{diam}}$  do
7:      $R_{1,2} \leftarrow R_{1,2} \cup \{r_1, r_2\}$ 
8:      $r_2 \leftarrow r_2 + \Delta r$ 
9:   end while
10:   $r_1 \leftarrow r_1 + \Delta r$ 
11: end while
12: return  $R_{1,2}$ 
```

Algorithm A2 ReduceSearchSpace($R_{1,2}, \Delta\theta, D_{\min}, D_{\max}, \text{turb}_{\text{diam}}, N_\theta$)

```
1:  $\Theta \leftarrow \emptyset$ 
2: for  $(r_1, r_2) \in R_{1,2}$  do
3:    $\Theta_{r_1, r_2} \leftarrow \text{GetBestAngles}(r_1, r_2, \Delta\theta, D_{\min}, D_{\max}, \text{turb}_{\text{diam}}, N_\theta)$ 
4:    $\Theta \leftarrow \Theta \cup \Theta_{r_1, r_2}$ 
5: end for
6: return  $\Theta$ 
```



Algorithm A3 GetBestAngles($r_1, r_2, \Delta\theta, D_{\min}, D_{\max}, \text{turb}_{\text{diam}}, N_\theta$)

```

1: farms  $\leftarrow \emptyset$ 
2:  $\Theta_{r_1, r_2} \leftarrow \emptyset$ 
3:  $\theta_1 \leftarrow -\frac{\pi}{2} + \Delta\theta$ 
4: while  $\theta_1 \leq \frac{\pi}{2}$  do
5:    $\theta_2 \leftarrow -\frac{\pi}{2}$ 
6:   while  $\theta_2 \leq \theta_1 - \Delta\theta$  do
7:      $d_{\text{grid}} \leftarrow \min_{z \in Z_*^2} \left\| P_{B_0}^{\mathcal{B}(\theta_1, \theta_2, r_1, r_2)} z \right\|$ 
8:     if  $(d_{\text{grid}} \geq D_{\min} \cdot \text{turb}_{\text{diam}}) \wedge (\theta_1 - \theta_2 \leq \pi - \Delta\theta)$  then
9:        $n \leftarrow 1$ 
10:      for  $i = 0$  to  $i = 1$  do
11:        for  $j = 0$  to  $j = 1$  do
12:           $\mathbf{F}_4(n) \leftarrow P_{B_0}^{\mathcal{B}(\theta_1, \theta_2, r_1, r_2)} \binom{i}{j}$ 
13:           $n \leftarrow n + 1$ 
14:        end for
15:      end for
16:       $\text{aep} \leftarrow \mathbb{E}_W [\mathcal{P}(\mathbf{F}_4, w_s, w_d)]$ 
17:       $\text{farms} \leftarrow \text{farms} \cup \{(\theta_1, \theta_2, \text{aep})\}$ 
18:    end if
19:     $\theta_2 \leftarrow \theta_2 + \Delta\theta$ 
20:  end while
21:   $\theta_1 \leftarrow \theta_1 + \Delta\theta$ 
22: end while
23: sort(farms) {by decreasing order of aep}
24: for  $i = 1$  to  $i = N_\theta$  do
25:    $\Theta_{r_1, r_2} \leftarrow \Theta_{r_1, r_2} \cup \{(\text{farms}(i). \theta_1, \text{farms}(i). \theta_2)\}$ 
26: end for
27: return  $\Theta_{r_1, r_2}$ 

```



Algorithm A4 GenerateConfigs($R_{1,2}, \Theta, D_{\min}, D_{\max}, \text{turbdiameter}$)

```
1: grids  $\leftarrow \emptyset$ 
2: for  $(r_1, r_2) \in R_{1,2}$  do
3:   for  $(\theta_1, \theta_2) \in \Theta$  do
4:      $d_{\text{grid}} \leftarrow \min_{z \in \mathbb{Z}_*^2} \left\| P_{B_0}^{\mathcal{B}(\theta_1, \theta_2, r_1, r_2)} z \right\|$ 
5:     if  $\min_{z \in \mathbb{Z}_*^2} \left\| P_{B_0}^{\mathcal{B}(\theta_1, \theta_2, r_1, r_2)} z \right\| \geq D_{\min} \cdot \text{turbdiameter}$  then
6:       grids  $\leftarrow$  grids  $\cup \{(r_1, r_2, \theta_1, \theta_2)\}$ 
7:     end if
8:   end for
9: end for
10: return grids
```

Algorithm A5 ComputeAllIntersections(grids, D_{\min}, Ω)

```
1: intersections_sets  $\leftarrow \{\emptyset\}$ 
2:  $n \leftarrow 1$ 
3: while  $n \leq \text{card}(\text{grids})$  do
4:   {Compute basic shape vector}
5:    $r_1, r_2, \theta_1, \theta_2 \leftarrow \text{grids}(n)$ 
6:    $v_1 \leftarrow (r_1 \cos(\theta_1), r_1 \sin(\theta_1))$ 
7:    $v_2 \leftarrow (r_2 \cos(\theta_2), r_2 \sin(\theta_2))$ 
8:   {Function of the intersections}
9:    $I_{v_1, v_2}(\Delta_1, \Delta_2) := \{k_1 v_1 + k_2 v_2 \in \mathbb{R}^2 \text{ s.t. } [k_1 v_1 + k_2 v_2 + (\Delta_1, \Delta_2)] \in \Omega; (k_1, k_2) \in \mathbb{Z}^2\}$ 
10:  {Compute offset maximising the number of admissible intersections}
11:   $(\Delta_1^*, \Delta_2^*) \leftarrow \arg \max_{\Delta_1, \Delta_2 \in [0, 1]^2} \text{card}(I_{v_1, v_2}(\Delta_1, \Delta_2))$ 
12:  {Add intersections to the set of intersections}
13:  if  $\text{card}(I_{v_1, v_2}(\Delta_1^*, \Delta_2^*)) \geq N_{\max}$  then
14:    intersections_sets  $\leftarrow \{(I_{v_1, v_2}(\Delta_1^*, \Delta_2^*), (r_1, r_2, \theta_1, \theta_2))\} \cup \text{intersections\_sets}$ 
15:  end if
16:   $n \leftarrow n + 1$ 
17: end while
18: return intersections_sets
```



Algorithm A6 GreedyInitialization(intersections)

```
1:  $(x_0, y_0) \leftarrow \arg \max_{x,y} \{x - y \text{ s.t. } (x, y) \in \text{intersections}\}$ 
2:  $\mathbf{F}_1(1) \leftarrow (x_0 \ y_0)$ 
3:  $n_t \leftarrow 1$ 
4:  $\text{intersections} \leftarrow \text{intersections} \setminus \{(x_0 \ y_0)\}$ 
5: while  $n_t < N_{\max}$  do
6:    $(x^* \ y^*)^\top \leftarrow \arg \max_{(x,y) \in \text{intersections}} \mathbb{E}_W \{\mathcal{P}(\mathbf{F}_{n_t} \oplus (x \ y), w_s, w_d)\}$ 
7:    $\mathbf{F}_{n_t+1} \leftarrow \mathbf{F}_{n_t} \oplus (x^* \ y^*)$ 
8:    $n_t \leftarrow n_t + 1$ 
9:    $\text{intersections} \leftarrow \text{intersections} \setminus \{(x^* \ y^*)\}$ 
10: end while
11: return  $\mathbf{F}_{N_{\max}}$ 
```

Algorithm A7 LocalSearch($\mathbf{F}_{N_{\max}}, \text{intersections}$)

```
1: convergence  $\leftarrow \perp$ 
2: aep  $\leftarrow \mathbb{E}_W \{\mathcal{P}(\mathbf{F}_{N_{\max}}, w_s, w_d)\}$ 
3: while  $\neg$  convergence do
4:    $\mathbf{H}_{N_{\max}} \leftarrow \mathbf{F}_{N_{\max}}$ 
5:   random_indices  $\leftarrow \text{shuffle}([0, \dots, N_{\max}])$ 
6:   for indice  $\in$  random_indices do
7:     {compute all possible layouts by moving  $i^{\text{th}}$  turbine}
8:     children_layout  $\leftarrow \text{generate\_children}(\mathbf{F}_{N_{\max}}, \text{indice}, \text{intersections})$ 
9:     for  $(\mathbf{G}_{N_{\max}}, \text{intersections}_G) \in$  children_layout do
10:      if  $\mathbb{E}_W \{\mathcal{P}(\mathbf{G}_{N_{\max}}, w_s, w_d)\} > \text{aep}$  then
11:         $\mathbf{F}_{N_{\max}} \leftarrow \mathbf{G}_{N_{\max}}$ 
12:        aep  $\leftarrow \mathbb{E}_W \{\mathcal{P}(\mathbf{F}_{N_{\max}}, w_s, w_d)\}$ 
13:        intersections  $\leftarrow$  intersectionsG
14:      end if
15:    end for
16:  end for
17:  convergence  $\leftarrow \mathbf{F}_{N_{\max}} = \mathbf{H}_{N_{\max}}$ 
18: end while
19: return  $(\mathbf{F}_{N_{\max}}, \text{aep})$ 
```



Algorithm A8 generate_children($\mathbf{F}_{N_{\max}}$, indice, intersections)

```
1: children_layout  $\leftarrow \emptyset$ 
2: for  $(x \ y) \in$  intersections do
3:    $\mathbf{G}_{N_{\max}} \leftarrow \mathbf{F}_{N_{\max}}$ 
4:   intersection $_G \leftarrow$  intersections
5:    $(x_{\text{new}} \ y_{\text{new}}) \leftarrow \mathbf{G}_{N_{\max}}(\text{indice})$ 
6:    $\mathbf{G}_{N_{\max}}(\text{indice}) \leftarrow (x \ y)$ 
7:   intersections $_G \leftarrow$  intersections $_G \setminus \{(x \ y)\} \cup \{(x_{\text{new}}, y_{\text{new}})\}$ 
8:   children_layout  $\leftarrow$  children_layout  $\cup \{(\mathbf{G}_{N_{\max}}, \text{intersections}_G)\}$ 
9: end for
10: return children_layout
```

Algorithm A9 PlaceTurbines(intersections)

```
1:  $\mathbf{F}_{N_{\max}} \leftarrow$  GreedyInitialization(intersections)
2:  $(\mathbf{F}_{N_{\max}}, \text{aep}) \leftarrow$  LocalSearch( $\mathbf{F}_{N_{\max}}$ , intersections)
3: return  $(\mathbf{F}_{N_{\max}}, \text{aep})$ 
```

Algorithm A10 Aligned_Optimization($\Omega, N_{\max}, N_{\theta}, D_{\min}, D_{\max}, \Delta r, \Delta \theta$)

```
1:  $R_{1,2} \leftarrow$  GenerateR1R2( $\Delta r, D_{\min}, D_{\max}$ )
2: angles  $\leftarrow$  ReduceSearchSpace( $R_{1,2}, \Delta \theta, D_{\min}, D_{\max}, \text{turb}_{\text{diam}}, N_{\theta}$ )
3: grids  $\leftarrow$  GenerateConfigs( $R_{1,2}, \text{angles}, D_{\min}, D_{\max}, \text{turb}_{\text{diam}}$ )
4: intersections_sets  $\leftarrow$  ComputeAllIntersections(grids,  $D_{\min}, \Omega$ )
5: layouts  $\leftarrow \emptyset$ 
6: for  $(\text{intersections}, (r_1, r_2, \theta_1, \theta_2)) \in$  intersections_sets {Run in parallel} do
7:    $(\mathbf{F}_{N_{\max}}, \text{aep}) \leftarrow$  PlaceTurbines(intersections)
8:   layouts  $\leftarrow$  layouts  $\cup \{(\mathbf{F}_{N_{\max}}, \text{aep}, \text{intersections}, (r_1, r_2, \theta_1, \theta_2))\}$ 
9: end for
10: layouts  $\leftarrow$  sort(layouts) by aep in descending order
11: return layouts(0)
```

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Competing interests. The contact author has declared that none of the authors has any competing interests.

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