POSTER

Optimizing Wind Farm Project Assessments Using Genetic Algorithms

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Optimizing Wind Farm Project Assessments Using Genetic Algorithms

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Abstract

Offshore wind farms have emerged as a crucial component of renewable energy generation, offering higher energy production rates due to stronger and more consistent wind conditions. However, these advantages come with significant installation and maintenance costs, necessitating comprehensive optimization analyses of wind farms projects to ensure economic feasibility and maximize energy output. One of the most significant challenges in this context is the effective placement of wind turbines within an offshore wind farm, considering the historic wind intensity and direction of candidate areas, along with the impact of wake effects. This study presents a framework that integrates a genetic algorithm to optimize wind farm layouts with a simulation tool for evaluating configurations of wind farm projects. In this paper, we describe the optimization module implemented with genetic algorithms. The proposed approach demonstrates high modularity and achieves competitive results compared to established benchmarks, highlighting the effectiveness of our framework for optimization analysis in wind farm projects.

CCS Concepts

• **Computing methodologies → Genetic algorithms**; **Artificial intelligence**.

Keywords

Genetic Algorithms, Offshore Wind Farms, Optimization

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1 Introduction

A key challenge in implementing offshore wind farms is optimizing turbines placement, e.g., defining the wind farm layout, while accounting for restricted areas and associated costs. Turbine positioning directly influences implementation costs and, more critically, the efficiency of energy production, as wake effects and turbine interactions can substantially decrease overall power output. Wake losses are estimated to account for 10-15% of Annual Energy Production (AEP) in wind farms [4], leading to substantial energy deficit over the operational lifespan of a wind farm.

In this paper, we propose a modular framework for evaluating wind farms projects, enabling the modeling of various project-specific variables. The framework integrates two core components: (i) a genetic algorithm that explores different wind farm layouts to identify optimized configurations; and (ii) an interface to existing simulation tools, which allows us to estimate the wind farm energy output by specifying customizable components, including historical wind data, and turbine wake models. This approach assesses the energy output of each layout generated by the genetic algorithm, allowing for the identification of optimal configurations suited to potential implementation sites. This study provides an overview of the proposed framework and evaluates the performance of the developed genetic algorithm in optimizing wind farm layouts with respect to energy production.

2 Offshore Wind Turbine Placement Problem

Assessing the feasibility of an offshore wind farm requires careful analysis of potential sites, local wind distribution patterns, and the chosen turbine model, including its associated wake effects. This process involves evaluating various wind farm layouts to optimize energy output, taking all these factors into account. To support this task, the authors in [3] have proposed a wind farm simulation tool, allowing to incorporate: (i) various wake models based on turbine specifications; (ii) historical wind data for the candidate site; and (iii) multiple wind farm layouts. The simulator then estimates the expected energy output for the configured wind farm. Figure 1 illustrates an overview of the wind farm simulation tool component we incorporate in our framework.

Furthermore, the authors in [3] conducted a study in collaboration with the optimization community to generate benchmark scenarios for wind farm layout optimization. Their work involved two case studies: one with predefined wake models and another

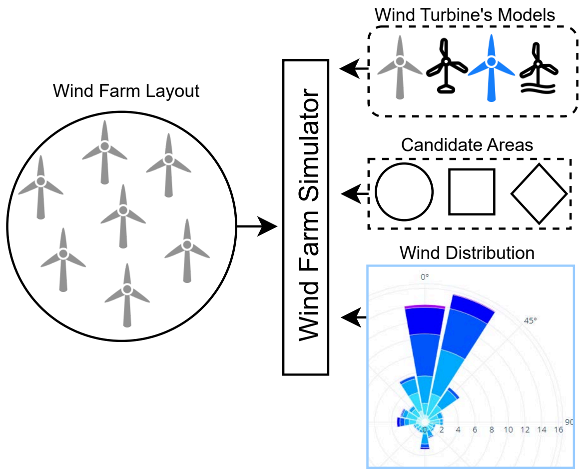

Figure 1: Overview for Wind Farm Simulation.

allowing participants to choose their own models. In this paper, we utilize the benchmarks from the first case study, which employs an analytical wake model and predefined components, comparing our results against their benchmarks.

3 An Optimization Approach using Genetic Algorithms

Our approach involves configuring predefined information about a candidate area, its wind probability distribution, and the turbine model within the simulator presented in Figure 1, originally proposed in [3]. We defined these variables based on those indicated in the first case study conducted by [3], which provides basis for comparison with the obtained benchmarks. We then apply genetic algorithms to generate and evaluate various wind farm layouts, integrating it with the simulator, and using the AEP output as the fitness value for each layout, e.g., the higher the energy output, the higher the fitness of the wind farm layout.

In the proposed approach, each agent (individual of the algorithm population) is modeled to represent a wind farm layout. Specifically, each agent is a vector of coordinates, $[(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)]$, where the coordinates (x_i, y_i) represent the position of the i-th turbine in the wind farm layout, and n is the number of turbines being considered for the project. This representation is compatible with the wind farm simulation tool, which is used to evaluate the agents' fitness, allowing us to identify layouts with better performance in terms of energy output, the primary optimization variable in our approach.

We use the following genetic operations adapted to the wind farm layout optimization problem [2]:

- **Selection**: This operation prioritizes better-performing agents, allowing them to reproduce more frequently than less fit ones. From the current population (set of candidate layouts), the algorithm selects a portion to undergo crossover and mutation operations.
- **Crossover**: This operation exchanges genetic information between two or more selected agents (candidate layouts) to create a new candidate solution. By combining turbines from different parents layouts, the algorithm generates new layout configurations that inherit traits from both parents, potentially improving the overall fitness of the population.
- **Mutation**: This operation introduces random changes to an agent's structure, simulating an erroneous self-replication. These small, random alterations help maintain genetic diversity within the population and prevent premature convergence to suboptimal solutions. In our approach, mutation randomically repositions turbines into the candidate layouts.

Figure 2 shows the proposed evolutionary approach also considering the integration with the wind farm simulation tool.

4 Evaluation

To evaluate our approach, we considered the 3 optimization problems from [3], contrasting our results to the benchmarks collected from participants by the authors. In Section 4.1, we describe a set of experiments conducted to understand the correlation between the parameters of the genetic algorithm. Based on these experiments, we define the parameters and the range of values to be explored in our hyperparameterization approach. In Section 4.2, we then execute the proposed method to the 3 optimization problems from [3], comparing the results obtained.

4.1 Parametrization

A common challenge when using evolutionary algorithms, such as genetic algorithms, is selecting the appropriate parameters to guide the algorithm toward optimal solutions while avoiding premature convergence [8]. The genetic algorithm implemented in our approach utilizes the following parameters [6]: *population*, which specifies the size of the agent population; *cxpb* (crossover probability), which represents the likelihood of two agents being mated; *ngen*, the maximum number of generations; and *mutpb* (mutation probability), which denotes the probability of an agent undergoing mutation. Additionally, when either a mating or mutation event occurs, further parameters must be considered. In case of mating, the parameter *alpha* determines the proportion of genetic material exchanged between agents. In case of mutation, the parameter *indpb* (individual probability) regulates the extent to which the genetic material of a single agent is subject to mutation. When a mutation occurs, affecting either a specific gene or the entire genetic sequence, a random value is sampled from a Gaussian distribution characterized by a mean of μ and a standard deviation of σ, which is subsequently added to the gene. The selection genetic operator employed is the *tournament* method, which selects the best-fit agent from a pool of k agents. These parameters collectively govern the evolutionary process, influencing the convergence and diversity of solutions within the population.

To understand the correlation between these parameters for this specific problem, we arbitrarily conducted 18 experiments, which was a reasonable amount to gain insights into the algorithm's behavior, configuring randomly the parameters across different ranges and extracting both positive and negative correlations. A correlation analysis was initially performed to assess the relationship between the parameters and the resulting fitness, i.e., AEP. The results indicated that *cxpb* had a strong positive correlation with AEP (0.77), while *indpb* exhibited a significant negative correlation (-0.68), and *mutpb* showed a weaker negative correlation (-0.25).

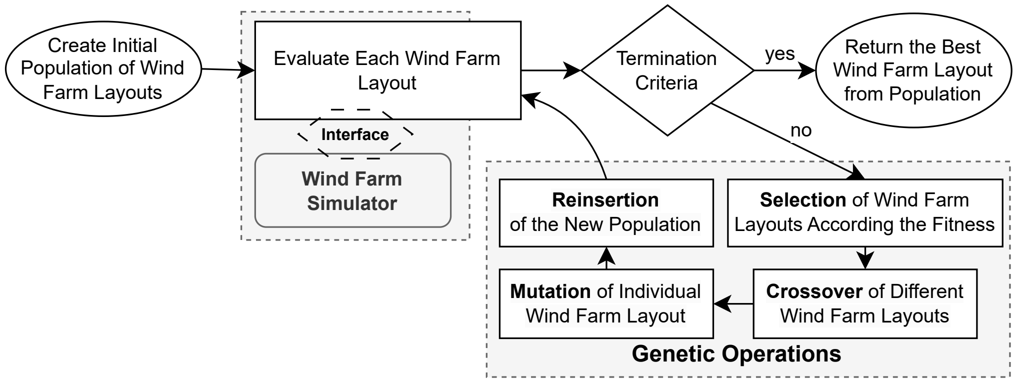

Figure 2: Proposed Evolutionary Approach.

Based on these findings, a hyperparameter search was conducted by varying *cxpb*, *indpb*, and *mutpb* within the continuous range of 0 to 1, in increments of 0.05. The remaining parameters were arbitrarily fixed during the hyperparameter tuning. This strategy allowed for refining the parameter values to optimize AEP.

4.2 Results

To evaluate our framework and compare our results with the benchmark available in [3], we use the same wake model employed by other participants, applying the following constants in the wake model:

- Thrust coefficient (C_T): 8/9.
- Rotor turbine diameter (D): 130 m.
- k_y, relating to a turbulence intensity of 0.075: 0.0324555.

We used the same 3 optimization problems for wind farm layout from [3], comprising 16, 36, and 64 turbines, placed within circular sites of 1,300, 2,000, and 3,000 meters in radius, respectively. To determine the parameter values that maximize the fitness, proximally 1,330 experiments were conducted by varying *cxpb*, *mutpb*, and *indpb* for each scenario presented in [3]. The remaining algorithm parameters were chosen arbitrarily. The ranges defined for each parameter were: *cxpb* varying between 0.50 and 1.00, *mutpb* between 0.25 and 0.75, and *indpb* between 0.15 and 0.65, with a step of 0.05 for each parameter. These limits were chosen to focus on regions of greatest influence on the algorithm's performance, as identified in preliminary experiments. The best parameters found for each scenario [3] are gathered in Table 1.

Table 1: Final GA parameters for the different scenarios.

Turb.	cxpb	mutpb	Pop	Tourn	alpha	Gen	indpb	sigma	mu
16	0.95	0.55	300	5	0.5	1500	0.55	100	0
36	0.95	0.35	300	5	0.5	1500	0.35	100	0
64	0.80	0.75	300	5	0.5	1500	0.40	100	0

Under ideal conditions, the AEP for a given wind farm configuration is calculated by summing the individual contributions of each turbine's power output over 8,760 hours (representing one year). Thus, the resulting maximum AEP values for each optimization problem are 469,536 MWh, 1,056,456 MWh, and 1,878,144 MWh for 16, 36 and 64 turbines, respectively.

Tables 2, 3, and 4 rank the AEP values obtained by our approach for each optimization problem compared to those reported by other participants in [3]. Among the 10 solutions presented in the study [3], 6 are Gradient-based approaches (G) and 4 are Gradient-Free[1] approaches (GF). One solution (the 12th row in the tables) represents an example layout provided by the authors of the study [3], and another solution (highlighted in yellow) is our solution based on genetic algorithms, which is also a GF method. Our approach demonstrated competitive performance across the different scenarios, yielding AEP values that, while not always surpassing all other methods, consistently positioned the genetic algorithm within a respectable range of solutions.

Table 2: Comparative results for the 16 turbines scenario

Rank	Algorithm	Grad.	AEP (MWh)	Increase
1	SNOPT+WEC	G	418,924.4064	14.17%
2	Our Approach	GF	416,897.7293	13.61%
3	fmincon	G	414,141.2938	12.86%
4	SNOPT	G	412,251.1945	12.35%
5	SNOPT	G	411,182.2200	12.06%
6	PSQP	G	409,689.4417	11.65%
7	Multistart Interior-Point	G	408,360.7813	11.29%
8	Full Pseudo-Gradient Approach	GF	402,318.7567	9.64%
9	Basic Genetic Algorithm	GF	392,587.8580	6.99%
10	Simple PSO	GF	388,758.3573	5.95%
11	Simple Pseudo-Gradient Approach	GF	388,342.7004	5.83%
12	(Example Layout)	-	366,941.5712	-

Table 3: Comparative results for the 36 turbines scenario

Rank	Algorithm	Grad.	AEP (MWh)	Increase
1	SNOPT+WEC	G	863,676.2993	17.05%
2	Our Approach	GF	854,895.9156	15.85%
3	Multistart Interior-Point	G	851,631.9310	15.42%
4	PSQP	G	849,369.7863	15.11%
5	SNOPT	G	846,357.8142	14.70%
6	SNOPT	G	844,281.1609	14.42%
7	Full Pseudo-Gradient Approach	GF	828,745.5992	12.31%
8	fmincon	G	820,394.2402	11.18%
9	Simple Pseudo-Gradient Approach	GF	813,544.2402	10.25%
10	Basic Genetic Algorithm	GF	777,475.7827	5.37%
11	Simple PSO	GF	776,000.1425	5.17%
12	(Example Layout)	-	737,883.0985	-

Notably, in the 16, 36, and 64-turbine scenarios, the algorithm achieved an AEP increase of 13.61%, 15.85%, and 14.26%, respectively, compared to the example layout provided, achieving second

[1]Gradient-based methods use function slopes for faster optimization, while gradient-free methods work without gradients, making them suitable for complex, non-smooth problems.

Table 4: Comparative results for the 64 turbines scenario

Rank	Algorithm	Grad.	AEP (MWh)	Increase
1	SNOPT+WEC	G	1,513,311.1936	16.86%
2	PSQP	G	1,506,388.4151	16.36%
3	Multistart Interior-Point	G	1,480,850.9759	14.35%
4	Our Approach	GF	1,479,753.2366	14.26%
5	SNOPT	G	1,476,689.6627	14.03%
6	Full Pseudo-Gradient Approach	GF	1,455,075.6084	12.36%
7	SNOPT	G	1,445,967.3772	11.66%
8	Simple Pseudo-Gradient Approach	GF	1,422,268.7144	9.82%
9	Simple PSO	GF	1,364,943.0077	5.40%
10	fmincon	G	1,336,164.5498	3.18%
11	Basic Genetic Algorithm	GF	1,332,883.4328	2.93%
12	(Example Layout)	-	1,294,974.2977	-

place to 16 and 36-turbine scenarios, and fourth place to the 64-turbine scenario. When considering only others GF methods, our approach outperformed all other methods for the three optimization scenarios. Considering the maximum possible energy output for each set of wind turbines, our approach achieves 88.79%, 80.92%, and 78.79% of the maximum output for the 16, 36, and 64-turbine scenarios, respectively. In contrast, the best solution presented in [3] (SNOPT+WEC) achieves 89.22%, 81.75% and 80.57%, respectively. This deviation from maximum generation is seen across all methods and is attributed to the restricted area relative to the number of turbines.

These results highlight the potential of genetic algorithms to provide viable, near-optimal solutions in complex optimization problems [2], especially in the context of renewable energy system design. Also, the results validate the optimization component of the proposed framework.

5 Related Work

Various optimization techniques have been applied to the Wind Farm Layout Optimization (WFLO) problem. In this section, we describe the GF approaches used by participants in the study [3]: (i) Pseudo-Gradient Method: this method represents turbine interactions with vectors proportional to the wind speed deficit caused by wake effects. These vectors substitute traditional gradients in optimization algorithms, enabling efficient turbine layout adjustments [9]. (ii) Particle Swarm Optimization Method: this method optimizes wind farm layouts to increase annual energy production. By using random initial particles for layout, this approach effectively navigates the complex non-convex solution space, minimizing the risk of local optima and enhancing overall energy output [1]. (iii) Genetic Algorithm Using a Matrix Representation: this method employed other coding approach in the genetic algorithm, using binary matrices instead of numerical chromosomes. Each chromosome is represented as a 10x10 matrix, where a '1' indicates the presence of a turbine and a '0' indicates its absence in a given cell. This coding method significantly reduced computational time and enhanced optimization results [5]. (iv) Multi-Population Genetic Algorithm (MPGA): this method incorporates standard genetic operators while introducing new concepts of immigration and coevolution. Immigration refers to the exchange of individuals between subpopulations, which promotes genetic diversity and allows better solutions to spread across the populations. Coevolution enables multiple populations to evolve simultaneously, facilitating the retention of elite individuals and enhancing overall solution quality [7].

6 Conclusion

In this work, we proposed a framework to addresses wind farm optimization by dividing it into modular components. This approach enables the independent modeling of turbine characteristics, site wind conditions, objective functions, and other relevant factors. The optimization component employs genetic algorithms to search for optimal wind farm layouts based on the configured inputs.

While this paper focuses on layout optimization for individual candidate areas, the framework is adaptable for evaluating energy-optimized outputs across multiple sites, turbine models, and layout configurations. By considering these elements, our approach offers a valuable decision-support tool for wind farm projects.

In our evaluation, the proposed approach showed good performance compared to the benchmarks available in [3], outperforming all others gradient-free (GF) methods, and being competitive with gradient-based (G) methods, while retailing flexibility to incorporate additional optimization criteria. In future work, we plan to explore multi-criterion optimization, including cost components and cabling considerations [10].

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