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Gradient-based multidisciplinary design of wind farms with continuous-variable formulations

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HIGHLIGHTS

- A gradient multi-objective optimization algorithm is proposed for WFLO problems.
- The problem formulation includes energy, land, cabling and environmental impact.
- Exact gradients are derived for the optimization objectives and constraints.
- NSGA-II is unable to cover the solution space of high-density wind farms.
- The proposed approach outperforms NSGA-II in coverage, spread and efficiency.

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ABSTRACT

In addressing the multi-criteria Wind Farm Layout Optimization (WFLO) problem, the literature has been focused on the simple weighted sum approach using single-objective stochastic and evolutionary algorithms, in addition to Pareto formulations using evolutionary algorithms. There is no single solution to a multi-criteria problem with conflicting objectives; therefore, the Pareto approach is useful to provide the developer with a non-dominated set of solutions. However, the evolutionary optimization algorithms tend to be computationally prohibitive, especially when optimizing large-scale wind farms. Additionally, most of WFLO problems are highly constrained, where many unfeasible zones can exist inside the proposed wind farm boundaries, which in turn complicates the optimization process. To remedy these drawbacks, we propose a gradient-based approach to Pareto optimization of the multi-criteria WFLO problems considering land footprint, energy output, electrical infrastructure and environmental impact. Mathematical functions and their derivatives are developed to represent the four objectives, land-based constraints, and their gradients. The developed models were validated by devised numerical experiments; and the optimized layouts using the proposed algorithm were compared to those by the Non-Dominated Sorting Genetic Algorithm (NSGA-II). Our results provide some evidence regarding the inability of the NSGA-II to cover the objective space when optimizing wind farms with large power-densities. In contrast, our proposed approach succeeds in obtaining high-density layouts efficiently. Furthermore, we demonstrated the superiority of the developed algorithm, in the aspects of coverage, spread, and computational cost.

1. Introduction

The Wind Farm Layout Optimization (WFLO) problem was firstly formulated by discretizing the farm land into square cells with a node at the center, and defining the decision variables as binary, using “1” or “0” to represent whether a turbine is located at the node or not, respectively [1,2]. This discrete representation does not allow exploring the interspaces between the fixed nodes, which in turn makes the theoretical optimal solution far from true optimality. Furthermore, increasing number of nodes would increase the complexity of the NP-hard problem as the number of possible solutions is 2^n, where n is the number of nodes. An advantage of using this representation is the potential benefit of fast computation by mathematical programming. However, the computational cost that is required for optimizing moderate number of turbines with Mixed Integer Linear Programming (MILP) and

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Quadratic Integer Programming (QIP) would be prohibitive as reported by Turner et al. [3]. This is why the discrete representation has been quickly replaced by a continuous representation for the decision variables which represent the Cartesian coordinates of the turbines, e.g., [4,5]. Thus, by utilizing the continuous formulation, the whole farm can be explored for the turbines' placement by using real-coded optimization methods. The two representations of discrete and continuum domains are illustrated in Fig. 1.

The first iteration to solve the WFLO was done by Mosseti et al. [1], where the problem is formulated based on a discrete representation and solved by using a binary coded genetic algorithm (GA). Following Mosseti et al.'s pioneering work, the literature has flowed in the direction of using GAs for design optimization of wind farms, as GAs are generally less likely to be entrapped in a local optimum because of their design space exploration capability [6]. However, diversity-enhancing mechanisms may be needed to facilitate that [7]. In addition, a local search procedures may be required after a GA run to truly reach the nearest local optimum. These implementations add to the prohibitive computational cost of the basic algorithms. For instance, Gao et al. [8,9] used a multi-population GA for better exploration of the design space. Huang [10] used a hybrid approach using GA and a hill-climbing method to refine the final solution by GA, while Rahbari et al. [11] proposed a hybrid method of GA and a multilevel technique to improve the initial population. Another attempt to increase the quality of obtained solutions was done by Saavedra-Moreno et al. [12], seeding the initial population of the genetic algorithm with solutions obtained by a greedy heuristic method. In addition, Réthoré et al. [13] proposed a multi-fidelity approach combining GA and sequential linear programming. Furthermore, other stochastic methods have been implemented, such as Differential Evolution [5], Particle Swarm Optimization [4,14–18], Simulated Annealing [19] and Pattern Search [20]. Comprehensive reviews of previously proposed iterative methods for wind farm optimization are available for more details [21–25].

The wind farm optimization literature has overwhelmingly favored analytical, approximate, closed-form wake models (also known as "engineering" models) for optimization purposes. Although the availability of mathematical equations to model wake behavior allows to determine exact gradient and Hessian information, nonlinear mathematical programing methods have been applied only recently to optimize large-scale wind farm [26–28]. For instance, Park et al. [26] developed an engineering wake model and used sequential convex programming for optimization, while Guirguis et al. [27] used the most widely used Jensen's wake model with Gaussian modulation to make the velocity deficit function continuous at the wake boundary, thus enabling the use of an interior-point method (IPM) for optimization. In [27], we have demonstrated the potential of nonlinear mathematical programing to solve the WFLO problem more efficiently than population-based methods such as GAs. While black-box optimization methods struggle in solving highly constrained problems efficiently, utilizing exact gradient information with mathematical programing methods allows to obtain local optimal solutions quickly, and enables the exploration of the objective space when combined with well-designed multi-start algorithms [28].

The design process of large-scale wind farms is a challenging task. Many factors should be considered for optimal micrositing of wind turbines, such as wake turbulence that reduces power output and increases mechanical loads on wind turbine structures; installation cost; cost of civil and electrical infrastructures; overall land-footprint; and environmental concerns. Thus, a multidisciplinary design optimization approach is most appropriate for wind farm design [29].

While most of published works have considered produced power and turbines' construction cost (e.g. [1,2,20,30]), a few studies have taken into account other crucial decisive factors. For instance, the cost-of-energy models and the influence of landlord decision making were studied extensively by Chen el. [31–33]. Mora et al. [34] used the net present value as an indication for the profits, and added the turbines' selection to the decision parameters, employing a GA. Gonzalez et al. [35–37] studied the factors of the electrical and civil infrastructures intensively. Rodrigues et al. [21] elaborated more on the cost functions and electrical infrastructure, proposing a heuristic optimization framework. However, the used discrete domain representations, and hence their optimization approaches suffer from previously mentioned limitations. More details on the proposed multi-objective algorithms to wind farm layouts can be found in a recent review [29].

Another design objective that must be considered is land usage. Indeed, the power density (i.e., power output per unit of land area), is one of the main drawbacks of wind power technology, where a large area is required to produce a desired electric power; add to that, the cost of the used land and the requirements to construct the turbines far from inhabitants and wildlife. For example, Tong et al. [38] studied the trade-off between the wind farm efficiency and the land footprint using a mixed-discrete particle swarm optimization algorithm in continuous domain, in addition, the shape and orientation of the land have been considered in [39,40]. Furthermore, the produced noise propagation level has been considered as in [31,41].

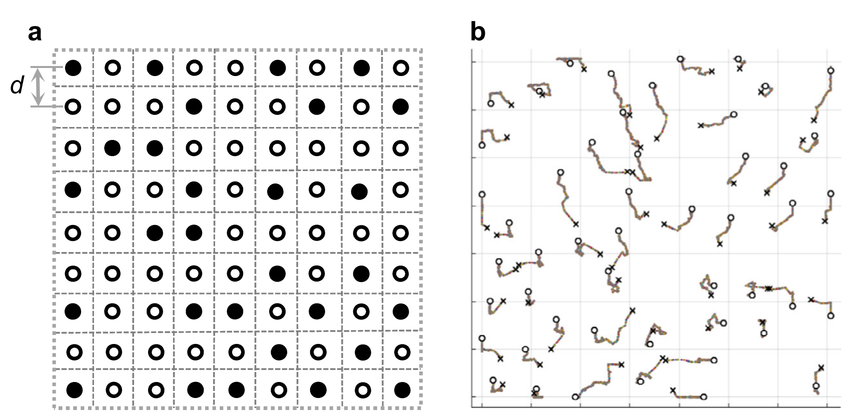

Fig. 1. Two approaches for WFLO domain representation: (a) Discrete representation where black circle represents turbines located at the center of the cell, and white circles represent empty cells. The distance *d* is the restricted space that cannot be explored during the optimization process; (b) Continuous-variable domain representation where, for example, the turbines could start from 'x' positions and make unrestricted moves during the optimization run till ending at 'o' positions.