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An advanced modeling system for optimization of wind farm layout and wind turbine sizing using a multi-level extended pattern search algorithm

Bryony DuPont [a, *], Jonathan Cagan [b], Patrick Moriarty [c]

[a] School of Mechanical, Industrial, and Manufacturing Engineering, Oregon State University, Corvallis, OR 97331, USA
[b] Department of Mechanical Engineering, Carnegie Mellon University, Pittsburgh, PA 15232, USA
[c] National Renewable Energy Laboratory, National Wind Technology Center, Golden, CO 80401, USA

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ABSTRACT

This paper presents a system of modeling advances that can be applied in the computational optimization of wind plants. These modeling advances include accurate cost and power modeling, partial wake interaction, and the effects of varying atmospheric stability. To validate the use of this advanced modeling system, it is employed within an Extended Pattern Search (EPS)-Multi-Agent System (MAS) optimization approach for multiple wind scenarios. The wind farm layout optimization problem involves optimizing the position and size of wind turbines such that the aerodynamic effects of upstream turbines are reduced, which increases the effective wind speed and resultant power at each turbine. The EPS-MAS optimization algorithm employs a profit objective, and an overarching search determines individual turbine positions, with a concurrent EPS-MAS determining the optimal hub height and rotor diameter for each turbine. Two wind cases are considered: (1) constant, unidirectional wind, and (2) three discrete wind speeds and varying wind directions, each of which have a probability of occurrence. Results show the advantages of applying the series of advanced models compared to previous application of an EPS with less advanced models to wind farm layout optimization, and imply best practices for computational optimization of wind farms with improved accuracy.

1. Introduction

As the population of the world grows and fossil fuel-derived electricity continues to be a significant cause of greenhouse gas emissions, it is imperative that clean alternative energy such as wind power is thoroughly explored. Increasing the incorporation of wind power into the national power development scheme will help to fulfill the substantial growth in power the United States is projected to require – a 39% increase during the next 20 years [1]. Additionally, the U.S. Department of Energy has presented the challenge to meet 20% of the U.S. total electricity demand using wind power by the year 2030 [1]. To meet this challenge, it will be increasingly important that newly developed wind farms are performing optimally; that is, they develop as much power as possible, while doing so at a reasonable cost. Other factors, such as local weather and topographical variation, must be considered to accurately predict wind farm performance prior to development, which can further break down barriers to establishing new wind farms. This challenge creates an opportunity to apply computational optimization algorithms that incorporate state-of-the-art modeling of power and cost to the design of prospective U.S. wind farms.

Though there has been significant research to date in the field of computational optimization as applied to wind farms (particularly to wind farm layout, or *micrositing*), research has only begun to approach the problem with the goal of developing real-world applicable results. To approach this real-world applicability, this work proposes an advanced modeling system that is designed to be employed within wind farm optimization algorithms; these advances are a significant step forward from research described in previous wind farm optimization literature in terms of model fidelity and inclusion. To utilize and validate the proposed advanced modeling system, it is employed within an improved Extended Pattern Search (EPS) algorithm, as the EPS has been successfully

* Corresponding author.
E-mail addresses: bryony.dupont@oregonstate.edu (B. DuPont), cagan@cmu.edu (J. Cagan), patrick.moriarty@nrel.gov (P. Moriarty).

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applied to wind farm micrositing optimization [2]. The advanced modeling system presented in this work includes:

a. A more accurate means of modeling cost, based on the National Renewable Energy Laboratory (NREL) Wind Cost and Scaling Model [3] [4], which estimates cost based on the parameters of turbine rotor radius and hub height.
b. The inclusion of wind shear (the variation of wind velocity with respect to height from the ground) in the calculation of effective wind speed and wake propagation.
c. The effects of atmospheric stability, considered in two ways: first, by accounting for the change in wind shear profile shape based on time of day and season, and second, by allowing variation in the wake decay constant based on atmospheric stability conditions, which is partially responsible for determining wake shape and wind speed deficit.
d. The consideration of partial wake interaction, which unlike many previous wind farm optimizations that treat turbine rotors as points, better represents overlapping wakes across the rotor-swept area.

These models, employed collaboratively as part of the objective used in the Extended Pattern Search–Multi-Agent System, help advance the state-of-the-art of analytical modeling for wind farm optimization. Each of these models is considered to be more accurate and representative of real-world conditions than previous models used for wind farm optimization [2]. Therefore, it is assumed that the results developed through the application of the advanced modeling system (and layouts subsequently optimized using the EPS-MAS) presented in this work will better predict wind farm performance prior to wind farm installation.

Employing the advanced modeling system, the EPS within a multi-agent system (MAS) algorithm accounts for each turbine's design activities. The agent approach is advantageous given that it facilitates multiple objectives and its architecture is highly adaptable, such that agents can be removed, added, or manipulated easily without altering other facets of the code [5]. This approach will be particularly beneficial considering proposed EPS-MAS work, which will account for the dynamic nature of the wind farm layout problem as new technologies, turbine designs, and local environmental factors are considered.

Previous approaches to solving the wind farm optimization problem—specifically those that include modeling variation from traditional test cases—are presented, along with a discussion of both the traditional EPS and the MAS approach utilized as a case study algorithm in this work. Next, the series of advanced models are presented – cost modeling, wake modeling, atmospheric stability, and power modeling. Then, the numerical procedure and formal methodology are shown, followed by results and discussion for both wind test cases.

2. Previous approaches

Previous literature in wind farm layout optimization generally focuses on maximizing the power development of the farm while minimizing cost. The first computational optimization approach to the wind farm layout optimization problem was performed by Mosetti et al., in 1994 [6], who established the framework upon which many subsequent optimization schemes were based. Within a genetic algorithm (GA) approach, Mosetti et al. used chromosomal strings that represented turbine position to create a discretized grid solution space. Grady et al. [7] improved upon this work by exploiting greater computational resources, allowing their GA to give superior results. Both of these optimization methods utilized the 2-D PARK model developed by Jensen [8] and minimize the objective of total cost of the farm while simultaneously maximizing power development.

As the most commonly utilized algorithm for the wind farm layout optimization problem, more advanced GA approaches have been widely applied, using a variety of objective functions and modeling approaches. A DGA (Distributed Genetic Algorithm) approach was developed by Huang [9]; while using the same discretized space and modeling as Mosetti et al. [6], the DGA was able to create layouts that develop more power, utilizing an objective function that maximized an estimate of wind farm profit. Huang then improved on the DGA by creating a Hybrid-DGA approach [10] that used both global and local objective functions. Wang et al. [11] developed a GA that improved on the discretization of previous work by allowing for varying shapes and coarseness of the solution space. Similar approaches were developed by Sisbot et al. [12] and Emami et al. [13], which expanded the use of GAs to solve the wind farm layout optimization problem by separating total farm cost and power development into distinct objectives, creating multi-objective optimizations that allow for focus on initial farm costs. Serrano-Gonzalez et al. [14] and Kusiak et al. [15] developed multi-objective evolutionary algorithm approaches (similar to a GA) that maximized the annual energy production of the farm; the latter created a more accurate measure of farm cost than cost modeling used in previous work. One shortcoming of these GA methods is the use of a discretized solution space, which limits the placement of turbines to defined cells, such that precise local placement is infeasible. Other researchers employing an evolutionary approach used heat-map style continuous space to enable more precise local placement [16].

In addition to genetic algorithms, multiple other methods have been used to solve the wind farm layout optimization problem. Particle swarm optimization algorithms are related to both biological swarming behaviors and evolutionary computation, and were used by Wan et al. [17,18] and Chowdhury et al. [19] to solve the wind farm optimization problem. Ozturk et al. [20] developed a different approach, a heuristic method, that utilized a weighted multi-objective function. These algorithms have a significant advantage over traditional GAs in their use of a continuous solution space, which the EPS-MAS also employs. Other algorithms applied to wind farm layout optimization include the simulated annealing work presented by Bilbao et al. [21], and the mixed-integer nonlinear discrete combinatorial optimization algorithm developed by Mustakerov et al. [22]. The EPS algorithm has also been successfully applied to wind farm layout optimization and has incorporated multiple advances in modeling that enable the development of more real-world applicable wind farm layouts, as introduced in this work and published in Refs. [2,23].

There are several recent works that seek to expand on the capability of various algorithms such that state-of-the-art modeling of cost, wake interaction, and power are incorporated into the optimization. Zhang et al. [24] created a cost surface to more accurately estimate the costs associated with wind farm development. Chowdhury et al. [25] established a framework for the selection of turbines with varying rotor radii, and DuPont and Cagan [23] expanded that capability by enabling an EPS algorithm to select both turbine hub heights and rotor radii. Benatiallah et al. [26] used actual long-term wind data as an input to their genetic algorithm for wind farm layout. Chen et al. [27] explored the implications of landowner decisions on resulting farm layouts. Kusiak et al. [15] used preliminary data mining in conjunction with a GA to determine the optimal control settings for a proposed farm. Kwong et al. explored wind farm layout optimization that considers noise propagation and limiting [28]. More recent work by Chowdhury et al. [29] used a Kernel Density Estimation to better model multimodal wind data. A large research collaborative (including Riso