Best Practices for Wake Model and Optimization Algorithm Selection in Wind Farm Layout Optimization.

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This paper presents the results of two discrete case studies regarding the Wind Farm Layout Optimization (WFLO) problem. Case study (1) considers variations in optimization strategies for a simplified Bastankhah Gaussian wake model, while case study (2) studies trade offs in performance with variation in both physics model and optimization strategy selection. For (1), a supplied wake model outputs Annual Energy Production (AEP) given participant input turbine locations. For (2), participants calculate AEP using a wake model of their choice, while also implementing their preferred optimization method. Participant submissions for optimized turbine locations were then compared to Large Eddy Simulator (LES) calculations for AEP, and results were measured for both quality and accuracy. Initial results for (1) show gradient-based methods, on average, superior to gradient-free methods in terms of convergence time and resultant AEP. Initial results for (2) show a pattern of linear turbine placement due to the permissive width of the wind farm given the turbine diameter and minimum spacing constraint. More participant data will be needed to see if trends seen in preliminary results are indicative of broader patters, or are anachronistic due to the smallness of the sample size.

I. Introduction

Optimizing turbine placement within a wind farm is a complex problem characterized by many local minima. The large number of inter-dependent variables involved in Wind Farm Layout Optimization (WFLO) create a design space that can quickly become intractable.

Two approaches have been taken to simplify the WFLO problem, as described by Padron et.al.[?] The first approach aims at improving the quality of individual models for wind farm attributes, i.e., aerodynamics, atmospheric physics, turbine structures, etc. As they go on to state, "The second approach is to improve the optimization problem formulation, and the algorithms [used] to solve the optimization."[?]

To better model the aerodynamics of the waked airflow region of a wind turbine, complex computational methods such as such as Direct Numerical Simulations (DNS) or Large Eddy Simulations (LES) have been developed. But the computational time these require for full simulation can be prohibitive in multi-iterative optimizations. Simplified Engineering Wake Models (EWMs) make certain limiting physics assumptions, resulting in greatly reduced computational costs.[?] Yet these simpler, less accurate approximations can sometimes lead to inefficient recommendations for turbine placement, due to what can be inaccurate assumptions in specific wind farm scenarios.

Given a single EWM, optimization methods to select ideal turbine locations are limited by characteristics of the functions governing the model. For example, EWMs that define a discontinuous wind speed behind wind turbines cannot be effectively used with gradient-based optimization methods, and models for which gradients have not been calculated are limited to gradient-free algorithms or gradient-based with finite difference derivatives. Additionally, within these limitations different optimization strategies have varying capacity to escape local minima in the pursuit of a global optimum.

To better understand the differences in EMW selection and optimization algorithm application, we have created two discrete case studies. These studies are designed to involve participants from many different research labs working on the WFLO problem. The first isolates optimization techniques for a single simplified EWM, the second observes the differences when combining variations in EWM selection and optimization method.

II. Methodology

Two of the major factors contributing to superior turbine placement recommendations are 1) EWM characteristics and 2) optimization algorithm. We have therefore designed two distinct case studies in an attempt to quantify the effects of alterations in each of these variables.

To isolate variability in the second factor (optimization method), we pre-coded a representative wake model as a control variable, and permit participants to use any optimization strategy they think will achieve

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the best results. This first scenario is called the Optimization Only Case Study, and is described below in ??.

Isolating the first factor of EWM variability proves more difficult. An EWM's compatibility with gradient-based or gradient-free optimization methods dictate which algorithms can be applied. As such, designing a case study which restricts participants to a single optimization algorithm would unnecessarily limit the scope of EWMs studied. With the aim of acquiring as much empirical data in order to determine best practices for the industry as a whole, our second case study permits participant selection of not only EWM, but also implemented optimization algorithm. It is called the Combined Physics Model/Optimization Algorithm Case Study, and is described below in ??.

To enable useful data from these two case studies, we needed a model wind farm with characteristics both restrictive enough to maintain simplicity, yet general enough to aid in solving and interpreting the results for more complex and realistic problems. The wind farm scenarios selected for the case studies are described below in ??

A. Optimization Only Case Study

The purpose of this case study is to determine the best optimization practices for WFLO, using a single representative EWM.

1. *Wake Model*

A simplified version of Bastankhah's Gaussian wake model[?,?] is used, since it is compatible with both gradient-based and gradient-free methods, and is computationally inexpensive in comparison to LES and DNS methods. This wake model is described by the following equations:

$$\frac{\Delta U}{U_\infty} = \left(1 - \sqrt{1 - \frac{C_T}{8\sigma_y^2/D^2}}\right) \exp\left(-0.5\left(\frac{y-\delta}{\sigma_y}\right)^2\right) \tag{1}$$

Where $\frac{\Delta U}{U_\infty}$ is the wake velocity deficit, $C_T = \frac{8}{9}$ and is the thrust coefficient, $y - \delta$ is the distance of the point of interest from the wake center in the cross-stream horizontal direction, D is the turbine diameter, and σ_y is the standard deviation of the wake deficit in the cross-stream horizontal direction as defined in ??:

$$\sigma_y = k_y(x) + \frac{D}{\sqrt{8}} \tag{2}$$

In ??, x is the downstream distance from the turbine generating the wake to the turbine of interest, and D is the turbine diameter. k_y is determined as a function of turbulence intensity (I). In this case study turbulence intensity is treated as constant, therefore we use $k_y = 0.0324555$.[?,?]

2. *Data File Type*

One request made by leaders of NREL's IEA37 Task group is to transition to implement their schema of .yaml format for all necessary data. This includes:

- Farm turbine attributes
- Farm turbine locaitons
- Farm wind frequency and wind speeds

There exists a separate working group refining the precise schema of these items, outside the scope of our case studies. Though they are a current work in progress, we implemented the most recent iteration of these files, and adapted them to our scenarios as necessary.

3. *Supplied Code*

The goal for participants in this case study is to discover the optimal turbine locations which maximize Annual Energy Production (AEP) for each specified farm.

To enable this, we created and supplied a pre-coded Python package. This package includes:

- Turbine charactersitics and wind frequency and speed in NREL's `.yaml` schema
- `.yaml` readers of the schema described above in ??.
- target function which calculates AEP, given participant input turbine locations and farm attributes

We selected the programming language Python since it is open source and widely used by researchers in the industry.

4. *Turbine*

To avoid complexity, we decided to use NREL's generalized 3.35MW reference turbine for all wind farms. It's attributes are open source, and is designed as a baseline for onshore wind turbine specifications.[?] The specifics of the turbine are located below, in ??:

Rotor Diameter	130	m
Turbine Rating	3.35	MW
Cut-In Wind Speed	4	m/s
Rated Wind Speed	9.8	m/s
Cut-Out Wind Speed	25	m/s

Table 1: Attributes for NREL's 3.35MW onshore reference turbine

5. *Farm Sizes*

Since some sizing and complexity variability effects optimization algorithm performance, three wind farm sizes are specified, of 16, 36, and 64 turbines. This is to avoid a bias towards algorithms optimized for wind farms of a specific size, and in order to observe how increased complexity correlates to convergence time and algorithm performance. Perfect squares were selected to permit grid turbine arrangements, if desired. For simplicity, the wind turbulence intensity constant was very small, at 0.075. Alteration by the participants to our specific code implementation was permitted if needed for compatibility with optimization methods, with the understanding that final wind farm layouts will be evaluated with original code that was provided.

With the calculations for AEP standardized, each participant ran the optimization algorithm and implementation of their choosing. Since there exists a great deal of variability in hardware, participants also reported processor speed, function calls, number of cores utilized, and amount of RAM installed the system utilized to find their optimized results.

6. *Farm Wind Frequency*

B. Combined Physics Model/Optimization Algorithm Case Study

This case study closely matched the one described in **??**, with the exception that no wake model was provided, and only a single wind farm size was to be optimized. Participants were free to chose their preferred EWM and optimization method. Comparison of participant results was based on:

1. **Quality:** Which participant results gave the highest LES-calculated AEP.
2. **Accuracy:** Which participant wake-model-calculated AEP most closely matched an LES-calculated AEP for the same turbine locations.

To limit LES computation time requirements when assessing results, the wind farm size for this case study was limited to 9 turbines. In addition to optimized turbine locations, participants reported which wake factors their model accounts for (i.e. turbulence, partial wake, shear, etc.), its governing equations' general characteristics (i.e. smooth, flat, Gaussian curve, presence of discontinuities, etc.), and any other relevant characteristics describing the model, to enable reproduction of results.

Since AEP calculations reported by different EWMs (which account for different physics phenomena) are not comparable, all participant-reported optimized turbine locations were run through the same LES. With the inherent bias each EWM has for its own optimized locations taken out, reported turbine locations were measured using the same simulation tool to compare AEP.

This study differs from the first, in that it assesses not only the optimization methods measured by previous case, but also the effects that different physics model approximations have on turbine location recommendations.

C. Wind Farm Attributes

1. *Wind Speed*

For simplicity in both scenarios, the freestream wind velocity was constant throughout the farm, at 13 m/s, regardless of turbine location or time of day.

2. *Wind Direction Frequency*

The wind direction probability mimics those found both in geographically linear canyons and also often at offshore locations using a bi-modal Gaussian distribution. This distribution is defined in **??** and the wind rose is shown below:

$$\begin{aligned} F = & w_1\left(\sqrt{\frac{1}{2\pi\sigma_1^2}}\right)\exp\left(-\frac{(\theta-\mu_1)^2}{2\sigma_1^2}\right) \\ & + w_2\left(\sqrt{\frac{1}{2\pi\sigma_2^2}}\right)\exp\left(-\frac{(\theta-\mu_2)^2}{2\sigma_2^2}\right) \\ & + w_2\left(\sqrt{\frac{1}{2\pi\sigma_2^2}}\right)\exp\left(-\frac{(\theta-\mu_3)^2}{2\sigma_2^2}\right) \end{aligned} \tag{3}$$

Where:

- θ: wind direction where north is 0°, measured clockwise.
- μ_1: first dominant wind direction (180°).
- μ_2, μ_3: second dominant wind direction (350° and −10°, respectively).
- σ_1: first standard deviation (20°).
- σ_2: second standard deviation (40°).
- w_1: first distribution weight (0.5).
- w_2: second distribution weight (0.5).

The wind rose shown below is a graphical depiction of the frequency from which direction on a compass (in degrees) the wind comes. A greater magnitude in the radial direction from the origin indicates a higher frequency from that direction.

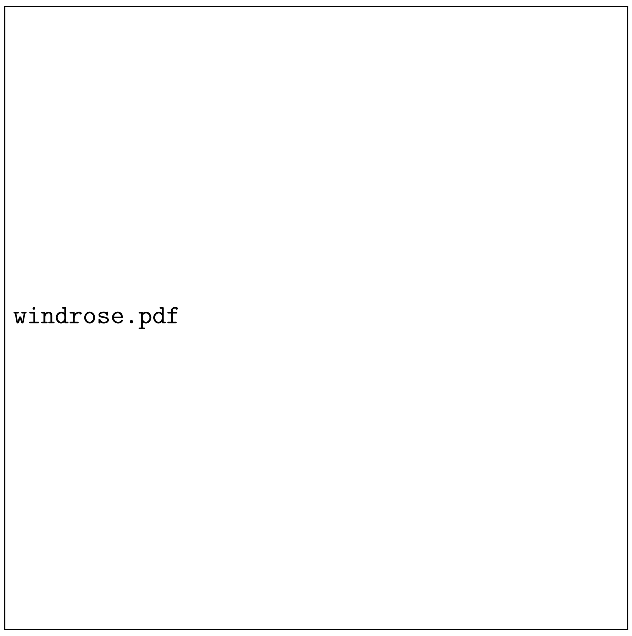

Figure 1: The wind frequency distribution; a bi-modal Gaussian distribution as defined in **??**

D. Analysis of results

1. Analysis of Optimization Only Case Study Results

2. Analysis of Combined Case Study Results

Not enough time/resources for LES right now.

Cross-Comparison of results was conducted.

III. Expected Results

IV. Conclusion

Appendix

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