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Wind farm layout optimization using a Gaussian-based wake model☆

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ABSTRACT

The wind farm layout optimization problem has received considerable attention over the past two decades. The objective of this problem is to determine the wind farm layout that maximizes the annual energy generated. The majority of studies that have solved this problem simulated the velocity deficit using the Jensen wake model. However, this model is not in agreement with field measurements and computational fluid dynamics simulations. In this study, an approach to solve the wind farm layout optimization problem based on a Gaussian wake model is proposed. The Gaussian wake model uses an exponential function to evaluate the velocity deficit, in contrast to the Jensen wake model that assumes a uniform velocity profile inside the wake. The proposed approach minimizes the annual cost of energy of a wind farm using a genetic algorithm. The application of the proposed approach yields higher annual generation and a lower computational time for all wind scenarios under study. Under a more complex wind scenario, the improvement was relatively small. This suggests that the use of a more robust wake model in the WFLO problem, does not lead to greater efficiency in real wind cases.

1. Introduction

The worldwide installed capacity of wind energy could be greater than 800 GW by the year 2020 if the trend continues. The World Wind Energy Association (WWEA) has reported that during the year 2015, more than 60 GW of capacity was installed, reaching an overall installed capacity of 434 GW worldwide [1]. Over the past decade, 38 GW of capacity on average has been installed annually worldwide. The general trend in wind energy use can primarily be attributed to the constant increase in the price of fossil fuels and the increasing social awareness of the impacts of greenhouse gas emissions on climate change [2]. The rapidly growing wind energy market has led to new challenges. For instance, a substantial portion of the onshore sites with the best wind resources are already being exploited; therefore, wind farm operators and designers are looking for new methods to make profits. As an example, advanced control methods such as model predictive control can effectively maintain constant power output while reducing mechanical loads on wind turbines, and therefore, reduce overall wind farm costs [3,4]. At the wind farm design stage, one of the most promising topics that has received considerable attention over the past two decades is wind farm layout optimization. Wind farm layout optimization leads to higher power efficiency, and therefore, higher energy generation per unit area.

The wind farm layout optimization (WFLO) problem, also known as the optimal wind turbine micro-siting problem, is a highly complex optimization problem that was first presented by Mosetti et al. [5]. The objective of this problem is to maximize energy production by locating wind turbines in such a way that the wake interference between them is minimized. The WFLO problem is a highly complex optimization problem that, even for a low number of turbines ($N_t < 30$), can have more than 10^{44} potential solutions. In addition, it is a mixed integer problem (has integer and continuous variables), is highly non-convex (has many optimal solutions) and cannot be represented in analytical form [6,7]. Therefore, this problem cannot be solved using traditional optimization methods, such as calculus-based methods. Most authors have decided to approach this problem using meta-heuristics, which are a family of optimization techniques that provide acceptable solutions to complex problems in a reasonable computational time. Genetic algorithms are the most commonly used meta-heuristics for approaching this problem because of their ability to avoid local optima in complex functions [8]. Other

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techniques to approach the WFLO include Particle swarm optimization [9–12], Ant colony optimization [13], Simulated annealing [14] and Artificial neural networks [15]. The high complexity of the problem is primarily due to the iterative evaluation of the velocity deficit caused by turbines in a wind farm, which must be calculated using an analytical wake model or by computational fluid dynamics (CFD).

The wake model proposed by Jensen [16,17], also known as the Park wake model, has been used in the vast majority of studies addressing the WFLO problem [7]. This model is very simple and it estimates the energy output accurately, as claimed by Katic et al. [17] [18]. However, field measurements of the velocity deficit in the wake of a wind turbine demonstrate that the velocity profile predicted by this model is unrealistic [19]. Due to the high complexity of the WFLO problem, it is not feasible to calculate the velocity deficit using computational fluid dynamics because the computational cost increases greatly, even for small problem instances. New analytic and semi-empirical wake models have been developed over the past decade. The velocity deficit described by these models is generally in agreement with computational fluid dynamics simulations and wind tunnel measurements [20–23]. These studies have demonstrated that the velocity profile in the wake of a wind turbine can be represented by a Gaussian curve [20,24]. In particular, Bastankhah and Porté-Agel [23] proposed a simple wake model that is based on a Gaussian curve and that only requires the specification of one parameter, the wake expansion factor k^*. This model has not been extended to the case of a wind farm with multiple wind turbines and has not yet been applied to predict the velocity deficit in the WFLO problem. In this study, the Gaussian-based wake model (GWM) proposed by Bastankhah and Porté-Agel [23] is extended to predict the velocity deficit in an entire wind farm, and subsequently, a method based on this wake model is proposed to approach the WFLO problem. A more robust approach for the WFLO problem can be developed using the GWM to calculate the velocity deficit. The proposed method uses a genetic algorithm to determine the individual positions of the turbines within a wind farm to minimize the annual cost of energy.

2. Gaussian-based wake model

Multiple studies have been conducted on the wake effect and turbulence caused by wind turbines. The studies that focused on modeling the wake of wind turbines can be classified into two classes: analytical models generally derived from empirical correlations and computational fluid dynamics-based models [7]. The second class includes methods based on large eddy simulation (LES) and Reynolds-averaged Navier-Stokes (RANS). These methods require considerable computational resources, making it practically infeasible to apply such methods within an iterative process, such as the wind farm layout design.

Analytical wake models are suitable for the WFLO problem because their computational cost is low and because it is easy to embed them within an optimization algorithm. The two most commonly used analytical models in WFLO studies are the model proposed by Jensen and the model proposed by Frandsen [5,25–28]. These models have been classified as top-hat models because they represent the velocity deficit in the radial direction by a discrete function. In fact, the velocity deficit some distance from the turbine rotor is approximately asymmetric [21,29] and resembles a Gaussian curve in the radial direction.

In this study, a wake model based on a Gaussian curve is used to predict the velocity deficit caused by wind turbines. This model was proposed by Bastankhah and Porté-Agel [23] and is based on the law of mass conservation and the law of momentum conservation. The GWM is based on the following equation for calculating the normalized velocity deficit:

$$\frac{\Delta u}{u_0} = C(x) f\left(\frac{r}{\delta(x)}\right), \tag{1}$$

where $C(x)$ represents the maximum normalized velocity deficit at a given downstream distance x. r is the radial distance measured from the center of the wind turbine, and $\delta(x)$ is the characteristic wake width at a given distance x. It is assumed that this characteristic wake width has a Gaussian shape, as shown in Fig. 1.

$$\frac{\Delta u}{u_0} = C(x) \exp\left(\frac{-r^2}{2\sigma^2}\right), \tag{2}$$

where σ is the standard deviation of the Gaussian-shaped velocity deficit at a given distance behind the turbine rotor. $C(x)$ is obtained by solving the equation of mass conservation and energy conservation, according to equation (3), where C_t is the thrust coefficient and d_0 is the rotor diameter:

$$C(x) = 1 - \sqrt{1 - \frac{C_t}{8(\sigma/d_0)^2}}. \tag{3}$$

Assuming a linear expansion of the wake region, as in Jensen's model, σ/d_0 can be obtained from the following equation:

$$\sigma/d_0 = k^* \frac{x}{d_0} + \varepsilon, \tag{4}$$

where $k^* = \delta\sigma/\delta x$ is the rate of growth of the wake and ε corresponds to the value of σ/d_0 when x tends to 0. Finally, introducing equations (3) and (4) into equation (2), the normalized velocity deficit is obtained through the following equation:

$$\begin{aligned}\frac{\Delta u}{u_0} = &\left(1 - \sqrt{1 - \frac{C_t}{8(k^* x/d_0 + \varepsilon)^2}}\right) \\ &\times \exp\left(-\frac{1}{2(k^* x/d_0 + \varepsilon)^2}\left[\left(\frac{z - z_h}{d_0}\right)^2 + \left(\frac{y}{d_0}^2\right)\right]\right),\end{aligned} \tag{5}$$

where z and y are the vertical and horizontal coordinates, respectively, and z_h is the hub height of the wind turbine. From equation (5), it follows that the calculation of the velocity deficit in the wake requires the determination of a single parameter (k^*). This parameter must be obtained from experimental data of the velocity profile, and therefore, varies with specific site parameters, such as the surface roughness (z_0) and turbulence intensity (I_0). For further details of the mathematical derivation of the model, refer to [23].

2.1. Comparison with Jensen's wake model

The GWM is simple, and it is in acceptable agreement with the LES simulations and wind tunnel measurements [23]. Bastankhah and Porté-Agel performed a comparison between the GWM wake model and two top-hat models (Jensen's [16] and Frandsen's [30]) in five case studies that involved miniature and real-scale wind turbines. In all cases, the velocity deficit calculated using the GWM was in acceptable agreement with LES simulations and wind tunnel measurements. In contrast, the top-hat models generally over predicted the velocity deficit in the center of the wake and under predicted the velocity deficit close to the edge of the wake.

Unlike Jensen's model [16], the GWM represents the velocity deficit with a continuous function in the radial direction. In Fig. 2, a comparison of the normalized velocity deficit calculated with both