Energy 121 (2017) 561–569

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

Wind farm multi-objective wake redirection for optimizing power production and loads

Mike T. van Dijk [a, *, 1], Jan-Willem van Wingerden [a, 2], Turaj Ashuri [b, 3], Yaoyu Li [c, 2]

[a] Delft Center for Systems and Control, Delft University of Technology, Mekelweg 2, Delft, 2628 CD, The Netherlands
[b] Department of Mechanical Engineering, Arkansas Tech University, 1811 N Boulder Ave, Russellville, AR, 72801, USA
[c] Department of Mechanical Engineering, University of Texas at Dallas, 800 W Campbell Rd, Richardson, TX, 75080, USA

ARTICLE INFO

Article history:
Received 12 October 2016
Received in revised form
19 December 2016
Accepted 9 January 2017
Available online 11 January 2017

Keywords:
Wind farm wake
Power optimization
Load mitigation
Wind energy
Yaw-misalignment

ABSTRACT

Clustering wind turbines as a wind farm to share the infrastructure is an effective strategy to reduce the cost of energy. However, this results in aerodynamic wake interaction among wind turbines. Yawing the upstream wind turbines can mitigate the losses in wind farm power output. Yaw-misalignment also affects the loads, as partial wake overlap can increase fatigue of downstream turbines. This paper studies multi-objective optimization of wind farm wake using yaw-misalignment to increase power production and reduce loads due to partial wake overlap. This is achieved using a computational framework consisting of an aerodynamic model for wind farm wake, a blade-element-momentum model to compute the power and the loads, and a gradient-based optimizer. The results show that yaw-misalignment is capable of increasing the power production of the wind farm, while reducing the loading due to partial wake overlap. A multi-objective optimization is able to further decrease the loads at the expense of a small amount of power production.

1. Introduction

Continuous research and development into the design and operation of renewable energy devices has lead to their global acceptance [1–6]. Despite these developments, the cost of traditional energy sources such as coal is still lower than renewable energy devices such as wind [7]. Therefore, the reduction of the cost of wind energy is still an important research topic [8–16].

Clustering wind turbines as a wind farm to share the infrastructure is an effective strategy to reduce the cost of energy [17,18]. This leads to aerodynamic interaction among the turbines [19]. As a turbine extracts energy from the wind, a speed deficit and increased turbulence occur in it's wake [20]. Downstream wind turbines located in such a wake produce less power and experience altered structural loading. This couples the power production and loading of upstream and downstream turbines. The significance of such coupling depends on the topology of the wind farm, wind direction and wake recovery time [21]. Since traditional control strategies aim to maximize the power production of the individual wind turbines, the total wind farm power production is sub-optimal [22].

Control strategies that take into account the wake effects are capable of mitigating this problem [23–29]. One method is to reduce the power extraction of an upstream turbine to improve the performance of the downstream turbines in its wake, thus increasing the total power production. Several studies investigated this method. Corten and Schaak [30] conducted a wind tunnel experiment of three arrays of eight model turbines and found that the total power extraction could be increased by reducing the power production of the upstream turbines. Heer et al. [31] optimized the wind farm energy output using a model predictive controller in combination with the Jensen [32] wake model. Marden et al. [33] increased the power output of the Horns Rev wind farm consisting of 80 turbines by 25%, using a model-free game-theoretic approach. Yang et al. [34] optimized an array of three wind turbines using an extremum seeking control algorithm in a nested-loop framework, from downstream to upstream units in a sequential manner. They used the Jensen model to simulate the wake dynamics. Behnood et al. [35] optimized the power production of a wind farm using particle swarm optimization algorithm. Horvat

---

* Corresponding author.
E-mail address: mikevandijk1@hotmail.com (M.T. van Dijk).
[1] Graduate student.
[2] Associate professor.
[3] Assistant professor.

http://dx.doi.org/10.1016/j.energy.2017.01.051
0360-5442/

et al. [36] used a sequential programming function of a wake model published by Brand [37]. Gebraad and van Wingerden [38] used a gradient-based algorithm to maximize the power production of a wind farm, simulated using a data-driven parametric model for wake effects [39]. Goit and Meyers [40] used a large-eddy simulation in combination with a gradient optimization algorithm to optimize a 10×5 wind farm. Finally, Serrano Gonzalez et al. [41] used a genetic algorithm in combination with a static wake model by Frandsen et al. [42] to optimize a row of wind turbines.

A recent approach is to redirect the wake of upstream turbines away from downstream turbines using yaw-misalignment. Several studies investigated this method. Churchfield et al. [43] found that the power extraction for an array of turbines increased by 10% when yaw-misalignment was imposed on the upstream turbines, using a large-eddy simulation. Gebraad et al. [44] maximized the power output of a simulated wind farm by yaw-misalignment using a game-theoretic optimization approach, and a data-driven parametric model for wake effects [39]. Using the same model, Fleming et al. [21] performed a combined optimization of lay-out and yaw control to improve the cost of energy of a wind farm. Park and Law [45] increased the power production of two model wind turbines during a wind tunnel test. They used a Bayesian optimization algorithm with yaw and blade pitch as inputs. Schottler et al. [46] found through a wind tunnel test of two scaled turbines that the power production of the downstream turbine was asymmetric with the yaw of the upstream turbine. Furthermore, they suggested that yawing the upstream turbine can increase the total power production.

Besides enhancing energy capture, yaw-misalignment can change the structural loads. Boorsma [47], and Ashuri and Zaaijer [48] found that the blade edgewise moments are mainly dominated by gravity force and are not heavily coupled with yaw-misalignment. Kragh and Hansen [49] suggested that the blade out-of-plane bending moments of upstream turbines decrease by a yaw-misalignment in the range of -10° to 30°. Similar results were found by Fleming et al. [50] using SOWFA [51]. They also discovered an increase in out-of-plane bending moments, drivetrain torsion and tower-base bending moments of the downstream turbine. These loads are likely caused by the transition from full to partial wake overlap. Jeong et al. [52] found that the fluctuation range of the root flapwise bending moment for a rigid blades can be reduced by 84.5% using a combination of yaw and pitch angle optimization. Churchfield et al. [43] showed an increase in the blade out-of-plane bending moments of downstream turbines due to yaw-misalignment. Kanev and Savenije [53] suggested that active wake control due to yaw-misalignment could significantly decrease the Damage Equivalent Loads (DEL) in a wind farm if partial wake overlap would not occur. Finally, Eggers et al. [54] found that wind shear significantly increased the rotor fatigue loads. Extending this to horizontal wind shear suggests partial wake overlap can similarly influence the fatigue loads.

As the literature shows, the yaw-misalignment has the potential to increase the power output of a wind farm. While the loads of upstream turbines may benefit from yaw-misalignment, downstream turbines can potentially experience increased loads due to partial wake overlap. To decrease the cost of wind energy, it is important to increase the power production without significantly reducing the lifetime of a wind turbine. Therefore, any application of control algorithms should not negatively impact the wind turbine loads.

This research studies how the topology of a wind farm affects the optimal yaw settings. A computational framework is utilized that models the wake effects, the power production of the wind farm, and the differential loading on individual wind turbines. Power production is maximized using yaw-misalignment, while mitigating the loading effects due to partial wake overlap.

The remainder of the paper is structured as follows. First, the computational framework that finds the power production of the wind farm and the wind turbine loads as a result of yaw-misalignment is presented. Then, results of a multi-objective wind farm optimization for a wide set of wind directions are presented. Finally, the results are discussed and followed by the conclusion.

2. Computational framework

This section presents the computational framework used to study the effect of wakes on the power production and loads. Fig. 1 shows the framework that consists of a wake model named FLORIS* (a modified version of the FLOw Redirection and Induction in Steady-state (FLORIS) model [39]), a blade-element-momentum model named CCBlade* (a modified version of CCBlade [55]), and an optimizer. All computational work is completed using Python on a Linux machine.

In the *FLORIS** module, the effective wind velocities and distributions in the lateral direction at hub height at each wind turbine are calculated. The module '*Find* Ω' determines the optimal rotor velocity for every turbine based on the effective wind velocity. The optimal rotor velocity and the velocity distribution are used to compute the power production and the loads at every turbine in the module *CCBlade**. The *Optimizer* combines the power production and the loads of the wind farm as one cost function, and it finds the optimal yaw settings. We use the NREL 5 MW baseline turbine for our study [56].

2.1. Wind farm aerodynamic wake

FLORIS* is a modified version of FLORIS, which computes the velocity distribution at hub height. FLORIS* is a data-driven model that describes the steady-state wake characteristics as a function of axial inductions and yaw-misalignment. It uses the velocity profiles to compute the power of each individual turbine. The wake is modeled using an augmented version of the Jensen model [32]. The wake deflection due to yaw-misalignment and rotational effects is characterized as in Jiménez et al. [57]. The fidelity of the model is increased by dividing the wake in three zones with individual expansion and velocity properties (Fig. 2). Although the model contains a small amount of parameters, it can be fitted to the time-averaged results from high-fidelity simulation data of wind farms. The computational efficiency in combination with the accuracy of the model makes it suitable for wind farm optimization purposes [58].

FLORIS* defines a local (x, y), and a global (x', y') coordinate system to allow modeling different wind directions Φ. The yaw γ_i of a turbine i is used to compute its wake deflection. For a wake caused by turbine j, the velocity in each corresponding wakezone z at the x-coordinate of a turbine i is defined by $U_{j,i,z}$, $z \in \{1, 2, 3\}$. FLORIS* computes the effective wind velocity, $U_{eff,i}$, at a downstream turbine i by combining all the overlapping wakes at its rotor. This is done by weighting the wake velocities $U_{j,i,z}$ by their overlap of the corresponding wake zones with the rotor swept area using the root-sum-square method of Katic et al. [59].

2.1.1. Velocity distribution

FLORIS* computes the velocity distributions at hub height which are used by CCBlade* to compute the differential loads. For this purpose, we introduce the set of indices $\mathscr{U} = \{1, 2, \ldots, N\}$ that number all turbines in a wind farm. Each turbine $j \in \mathscr{U} \backslash \{i\}$ has a velocity distribution over turbine i denoted by $\tilde{U}_{j,i}(y_{r,i})$. We define the local y-coordinate $y_{r,i}$ on the rotor disk of turbine i at hub height