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Model-free control of wind farms: A comparative study between individual and coordinated extremum seeking

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ABSTRACT

Large Eddy Simulations of the turbulent flow over an array of wind turbines have been performed to evaluate a model-free approach to power optimization. Two different implementations have been tested: (i) individual extremum-seeking control (IESC), which optimizes the power of the single turbines individually; (ii) nested ESC (NESC), which coordinates the single controllers to seek a farm-level optimum. Both schemes provide a gain over the baseline, which operates all the turbines with ideal design set-points. These settings are found to be sub-optimal for waked turbines. The NESC provides a slightly larger power production than the independent ESC, albeit it has a slower convergence to the optimum. Therefore, depending on wind variability, both strategies may be employed. IESC is more appropriate for sites with wind conditions changing on a short time scale, while NESC should be preferred when the wind conditions are quite stable. Since the extremum-seeking algorithm is model-free, uncertainties in atmospheric conditions, aging of the turbine or numerical dissipation due to the sub-grid model should not change the general conclusions reached in this paper. This methodology can provide reliable results and permits to gain, through the analysis, a useful knowledge on the mechanisms leading to the performance enhancement.

1. Introduction

In recent years, the deployment of large wind farms has enabled the wind energy industry to increase its penetration in electricity markets around the globe. Despite this promising trend, further reduction of the levelized cost of energy (LCOE) would be needed to attain the double-digit penetration levels set as targets in the U.S. and other countries. Advanced wind farm control strategies are essential to develop more profitable and cost-effective wind plants.

Wind plant operation in off-design conditions, such as turbines operating in waked conditions, represents an important challenge. As turbines are placed closer to one another, the wakes developing from windward turbines may not fully recover before impinging on the trailing turbines. These working conditions are likely to reduce energy capture and increase unsteady structural loads [1]. The development and assessment of control systems to mitigate the power losses due to wake interactions, and associated increase in fatigue loads, are areas of active research [2–11].

Various approaches have been explored in the literature, ranging from model-based optimization [2,3,5,9] to model-free methods [4,6,7,10]. Some of the proponents for model-based optimization have used simplified wake models. These engineering models are usually characterized by low computational cost and are suitable for real-time implementation and/or rapid tuning of control algorithms. However, these engineering models may present some shortcomings related to the assumptions necessary to simplify the physical description. Discrepancies in the predictions have been reported when optimal operating settings devised with static engineering models have been tested with higher-order aerodynamic simulation tools, such as large-eddy simulation (LES) [11,12].

The flow within wind farms— mainly because of wake interactions —is characterized by unsteadiness and a high degree of nonlinearity. Capturing the essential dynamics with simple computationally fast models remains a difficult task. For this reason model-free optimization, which does not rely on physical parameterizations of the plant, has also received attention in the field.

Model-free game theoretic methods have been proposed in Ref. [6]. In this work, the authors optimize the power production by adjusting the axial induction factor of each turbine using randomized learning algorithms. Starting from a baseline condition, the controller on each turbine randomly explores different set-point values for the induction factors. The optimal guess is

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updated when the newly-tested set-point increases the performance index, which is the power extraction of the whole wind farm or a subset of it. The performance of the algorithms is tested using the Jensen PARK model [13], which describes the flow in steady-state conditions only, and assumes that the turbines introduce wind velocity deficits that depend on the downstream distance from the rotors and the axial induction factors.

Model-free gradient-based methods have also been studied by various authors [4,7,10]. These algorithms use the gradient of the total power, or subsets of it, to guide the search for control variables toward the configuration that maximizes the wind-farm power. The algorithms in Refs. [4,7] optimize power by adjusting axial induction factors, while the method presented in Ref. [10] adjusts the available turbine controls (e.g., torque or blade pitch angle) to maximize power production. References [4,7] evaluate the solutions with dynamic versions of the PARK model, where the dynamics are introduced via time delays to capture wake propagation. Reference [10] uses *SimWindFarm* [14] for the evaluation of performance, which may also be viewed as a dynamic extension of the PARK model. In the MPPT method proposed in Ref. [4], the gradient of the power production with respect to axial induction factors is computed using backward finite difference based on the present and past values of the control variables. On the other hand, the extremum-seeking algorithms in Refs. [7,10] use an external dither perturbation on the control inputs to estimate the relevant gradient information for optimization. By proper selection of the dither signals, the approach in Refs. [7,10] can be made more robust to turbulent wind fluctuations. The implementation in Ref. [7] seeks to determine all optimization variables simultaneously. The approach in Ref. [10] takes advantage of a decomposition structure, rigorously justified in Ref. [9] using dynamic programming, to sequentially search for each control parameter until a solution is found. The sequential search in Ref. [10] is simpler to implement than the method in Ref. [7] and requires less communication between the turbines.

Overall, these studies showed the feasibility and potential for model-free optimization. However, algorithms have been evaluated using simplified models, such as *SimWindFarm* [14] or dynamic versions of the PARK model [13]. Given the state-of-art of high performance computing, it is plausible to evaluate model-free algorithms using more realistic computer models for the wind plant. Such an approach will not only provide more accurate wind flow state and turbine loadings, to better assess a control strategy, but will also enable deeper insights into the mechanisms behind the control solution.

In this paper, model-free Extremum-Seeking Control (ESC) is coupled with a Large Eddy Simulation (LES) of a wind farm consisting of three turbines aligned with the mean wind direction. This simple configuration is selected to evaluate one of the possible mechanisms used to manage wake interactions - shaping the induction zone of aligned turbines via control of the rotor speeds of each turbine [11]. Our work in this paper is motivated by the following question:

What advantages does coordinated extremum seeking control offer over the simpler case of applying extremum seeking control to each turbine without coordination?

To answer this question we consider two scenarios. In the first scenario, the extremum-seeking controllers on each turbine are set to enhance the power production of each individual turbine. We refer to this case as the *individual* ESC or IESC. In the second case, the turbine's control systems are coordinated in a nested structure, as proposed in Ref. [10], so that the performance index of an upstream turbine takes into account the presence of downstream waked turbines. We refer to this scenario as *nested* ESC or NESC. This nested architecture for coordination is consistent with the decomposition that results from applying dynamic programming to the (albeit static) optimization problem of maximizing wind farm power by jointly optimizing over all control inputs simultaneously [2,9].

In this work, generator torque control is used to maximize turbine power, as it is usual in Region 2 (below rated power) operations. Each turbine uses the same control law, where the generator torque is proportional to the square of the rotor speed [15–18]. The constant of proportionality is the so-called *torque gain*, which is the parameter adjusted in real-time by the IESC or the NESC for each turbine. The results from IESC and NESC are compared with a baseline reference that assumes the turbines are operating at their nominal peak efficiency under uniform inflow using the standard design value for the torque gain [16–18].

The main contributions of this paper are:

- Demonstrating ESC algorithms for power maximization in a LES of an array of aligned wind turbines.
- Adapting an ESC implementation from the literature [19] to power maximization in the presence of turbulence and propagation delays due to wake interactions.
- Providing data (to our knowledge, for the first time) from high-fidelity simulations to compare IESC with NESC, and elaborating on mechanisms for power extraction under waked conditions.

A comparison of the IESC and NESC with the previous results in the literature of model-free control of wind farms is not straightforward. In this paper, the control strategies are evaluated using LES as a virtual wind farm, while previous works [4,6,7,10] employ time-dependent wake models. On the same setup, LES and engineering models may yield different predictions [11,12]. This prevents a direct comparison with the published results. Furthermore, we use an available turbine control parameter (the torque gain) to maximize the power. In contrast, the works in Refs. [4,6,7] use the turbine's axial induction factor as the control variable. To convert a commanded axial induction factor into an available turbine control will likely require a turbine model and the effective wind speed at the rotor plane. In this regard, our work is closer to [10], although the present control algorithms are based on a more advanced (faster convergence) discrete-time version of ESC [19] than the one used in Ref. [10].

The remainder of the paper is organized as follows. Section 2 contains a brief description of the numerical code used to perform LES. Section 3 describes the ESC algorithms. The core ESC scheme as well as problem-specific modifications to take into account delays due to wake propagation are given. Key parameters of the case study are given in Section 4. The results are discussed in Section 5. Concluding remarks are presented in Section 6.

2. Numerical method

Large-eddy simulations have been performed using our in-house code UTD-WF. The main features of this code may be found in Ref. [12].

2.1. Navier-Stokes solver

The governing equations for the flow field are the filtered incompressible Navier-Stokes equations:

$$\frac{\partial U_i}{\partial x_i} = 0 \tag{1a}$$

$$\frac{\partial U_i}{\partial t} + \frac{\partial}{\partial x_j}(U_i U_j) = -\frac{\partial P}{\partial x_i} + \frac{1}{\mathrm{Re}}\frac{\partial^2 U_i}{\partial x_j \partial x_j} + \frac{\partial \tau_{ij}^{sgs}}{\partial x_j} + F_i \tag{1b}$$

where U_i is the i^{th} component of the velocity vector in the direction