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Hierarchical Control of a Wind Farm for Wake Interaction Minimization

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Abstract: The problem of controlling a wind farm for power optimization by minimizing the wake interaction among wind turbines is addressed. We aim to evaluate the real gain in farm power production when the dynamics of the controlled turbines are taken into account. The proposed local control enables the turbines to track the required power references in the whole operating envelope. Simulations are carried out based on a wind farm of 600 kW turbines and they show the actual benefit of considering the wake effect in the optimization algorithm.

Keywords: Wind farm, wake effect, wind turbines, power tracking, feedback linearization, predictive control.

1. INTRODUCTION

Technology and control methods for wind energy production through the use of wind turbines have nowadays reached a mature level of the state of the art. Variable-speed-variable-pitch wind turbines allow a good degree of adaptability to a wide range of wind conditions for the maximum power capture. Nonetheless, new challenges, as the ones posed by Europe 2020, and opportunities, thanks to developments in the field of control and optimization, have pushed the target further ahead towards a better exploitation of the wind source. For this reason, in recent years, we have witnessed a relevant increase in the installation of wind farms composed of several wind turbines, e.g. more than one hundred for some offshore wind farms. This in turns suggested to take in consideration aerodynamic interaction among the turbines when the power maximization of large wind farms is concerned. Indeed, when extracting kinetic energy from the wind, a wind turbine causes a reduction of the wind speed in the downstream wake. As a result a turbine, standing in the wake of an upstream one, experiences a reduction of available wind power (see Gebraad et al. (2013)). Intuitively as the number of wind turbines of a wind farm increases, the wake effect becomes more important, so that considering it when optimizing the wind production proves potential gain with respect to classic individual turbine maximum power point tracking (MPPT), (e.g. Park and Law (2015)). This mainly justifies a growing interest in *cooperative* methods to control wind turbines belonging to large wind farms.

One of the difficulties when dealing with wind farm power maximization subject to wake interaction lies in the solution of the optimization problem itself. This is mainly due to the lack of reliable models of the involved aerodynamic phenomena and, even when the latter are available, simplification is needed to let practical implementation feasible. Indeed, since a new optimization needs to be run each time that wind conditions change, one important feature of the optimization algorithm is fast convergence. As a result two main approaches to the optimization problem have been explored. On the one hand, model-free, data-driven methods have been employed by Marden et al. (2013), Gebraad et al. (2013), and Park and Law (2016), inspired by game theory and decentralized approaches. On the other hand, model-based optimization has been proposed, as in (Tian et al. (2014)), and (Park and Law (2015)), where a trade-off between model complexity and speed of convergence to a solution has to be taken into account. As stated by Marden et al. (2013), the aforementioned optimization algorithms assume the existence of local control strategies for individual wind turbines that can stabilize around any feasible optimal set point, solution of the wind farm optimization problem. Even if proving a potential benefit in the amount of extracted wind power, these assumptions are not necessarily realistic as either the dynamics of the optimization variables and the performance of the local controllers play an important role in the actual gain. In this paper we address the problem of maximizing a wind farm power production, based on a static optimization at high level for optimal set points generation and local control at low level to stabilize the wind turbines around them. Nonetheless we mainly focus on the local controller performance to demonstrate what can actually be achieved by means of the proposed hierarchical architecture. In literature few works have analyzed the effective gain of wind farm optimization under wake effect when the dynamics of the controlled turbines are considered. In (Heer et al. (2014)) a local controller based on system linear approximation is employed and it shows a

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1% energy gain with respect to classic *greed* control, where farm optimization would not be performed.

The central aspect that motivated this work is that, when cooperative optimization is employed, the optimal set points delivered to each turbine in the wind farm can deviate from the classic power references typically used in greed control. As it is well known, the former consist in the MPPT algorithm at low wind speed, and in stabilizing the power at its nominal value at high wind speed (see Ackermann (2005)). To do so, according to the current value of wind speed, references for the turbine rotor angular speed and for the pitch angle are obtained via the static aerodynamic relation between the mentioned variables and the aerodynamic power. However, when the desired aerodynamic power is lower than its optimal value, different set points for the rotor angular speed and the pitch angle must be provided. This is the case when considering the wake effect, as, to optimize the global power production, upstream turbines would degrade their *own* power production in order to increase the one of downstream turbines. Even though different strategies have been proposed in the literature for the choice of the *local* set points (e.g. Yingcheng and Nengling (2011), Žertek et al. (2012)), in the most cases the control architecture is based on standard linear controllers such as PID (e.g. Ramtharan et al. (2007)) and gain scheduling approaches (e.g. Wang and Seiler (2014)). To the extent of our knowledge, nonlinear techniques applied to the turbine control as in (Thomsen (2006)), and (Boukhezzar and Siguerdidjane (2011)) are conceived for well-defined operating modes, again either MPPT or power limiting at high wind speed. As a consequence their application for the entire turbine operating envelope as well as their extension to the more general task of tracking non conventional power references is not trivial. In this paper we employ a nonlinear control for power tracking, based on a combination of feedback linearization (FL) technique and model predictive control (MPC). The controller is applied to 600 kW turbines, and they are not confined to work in a specific region, i.e. no assumptions were made concerning the wind speed.

The rest of the paper is organized as follows. In Section 2 the wake and the wind turbine models are provided. The main control problem and its objectives are stated in Section 3. In Section 4 we present the proposed local control architecture. We carry out simulations to test performance at the wind farm scale in Section 5. The paper ends with conclusions and future perspectives in Section 6.

2. WIND FARM MODELING

This section is composed of two main parts. In the first one we consider an analytic representation of the wake model and the global wind farm power function. The reason is twofold. Firstly, this model will serve for the computation of the optimal set points via a gradient-based optimization. Secondly, we aim to use it for a dynamic simulation of the wind farm. In the second part we derive the wind turbine model. The composition of the two models let us describe the global wind farm functioning.

2.1 Wake model and global power function

The wake model describes the aerodynamic coupling among the wind turbines of a wind farm. In other words, it is a mathematical representation of the phenomenon according to which the wind blowing on the rotor disk of a given turbine is influenced by the free stream wind u_∞ blowing on the wind farm and by the operating conditions of all the upstream turbines. For the sake of simplicity we assume the wind speed u_∞ uniform and its direction ϑ^W constant. In addition, without loss of generality, we consider the wind turbines oriented in the direction of the free stream wind. This simplification is allowed mainly because the slow yaw angle γ dynamics is decoupled from the other turbine variables. It can be argued, though, that the optimal choice of γ values in a wind farm lead to a power production improvement, as shown by Park and Law (2015). Nonetheless, consideration of γ for wind farm optimization goes beyond the scope of this paper, which is to evaluate the actual power gain when the system *dynamics* is taken into account. For the same reason we do not aim to evaluate the effectiveness of the proposed approach with respect to less restrictive assumptions on the wind source. If the latter are to be considered the higher level optimization should be complexified, and this is subject of future work. As a consequence, for the stated purpose of this work, the turbine operating conditions having an impact on the wake effect can be represented via the induction factor $\alpha \triangleq (u_\infty - u_R)/u_\infty$, where u_R is the wind speed right behind the rotor disk of a turbine. Variable α serves as an indicator of the extracted power from u_∞. Indeed, the latter has a theoretical value of

$$P \triangleq \frac{1}{2}\rho\pi R^2 u_\infty^3 4\alpha(1-\alpha)^2\eta \tag{1}$$

where ρ is the air density, R the radius of the rotor disk, $\eta \in (0,1)$ the efficiency, and $C_p \triangleq 4\alpha(1-\alpha)^2$ the theoretical power coefficient. From the latter one can easily find the Betz limit $C_{p,Betz} = 0.59$ corresponding to a value of $\alpha_{Betz} = 1/3$. Note that operating a turbine at α_{Betz} corresponds to extracting the maximum power, i.e. MPPT. However, in real applications, C_p is typically provided in turbine specifications as a look-up-table, so that $C_{p,real} \cong C_p\eta$. In the sequel we make use of a continuous wake model presented by Park and Law (2015). Here we employ a simplified version of the latter, since for the choice we made, γ does not intervene in the model equations. The reader may refer to the aforementioned reference for a more complete description. According to the model, a turbine i, in a wind farm of N turbines, experiences a wind deficit with respect to u_∞ such that $u_i = u_\infty(1-\delta\bar{u}_i)$, where $\delta\bar{u}_i$ is the result of multiple wakes due to all the upstream turbines j with respect to turbine i. A widely used method to take into account multiple wakes is the conservation of kinetic energy (see Katic et al. (1986)) given by

$$\delta\bar{u}_i = \sqrt{\sum_{j=1|j\neq i}^{N} \delta\bar{u}_{ij}^2\varphi(i,j,\vartheta^W)}$$

where $\varphi(i,j,\vartheta^W) \triangleq \frac{1}{2}(1+sign(y_i'-y_j'))abs(sign(y_i'-y_j'))$ is a simple way to determine whether a turbine j is upstream with respect to the turbine i, $(j \rightarrow i)$, given a wind