A tutorial on control-oriented modeling and control of wind farms

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A TUTORIAL ON CONTROL-ORIENTED WIND FARM MODELING AND CONTROL

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Wind turbines are often sited together in wind farms as it is economically advantageous. However, the wake inevitably created by every turbine will lead to a time-varying interaction between the individual turbines. Common practice in industry has been to control turbines individually and ignore this interaction while optimizing the power and loads of the individual turbines. However, turbines that are in a wake experience reduced wind speed and increased turbulence, leading to a reduced energy extraction and increased dynamic mechanical loads on the turbine, respectively. Neglecting the dynamic interaction between turbines in control will therefore lead to suboptimal behaviour of the total wind farm. Therefore, wind farm control has been receiving an increasing amount of attention over the past years, with the focus on increasing the total power production and reducing the dynamic loading on the turbines. In this chapter, wind farm control-oriented modeling and control concepts are explained. In addition, recent developments and literature are discussed and categorized. This chapter can serve as a source of background information and provides many references regarding control-oriented modeling and control of wind farms.

Parts of this chapter have been published in (Boersma et al., 2017).

2.1. INTRODUCTION

This chapter is, with respect to the literature overview presented in (Knudsen et al., 2015), focused on the corresponding flow control problem and discusses recent wind farm research developments and field test experiments in more detail. It is organized as follows. In §2.2, a brief introduction to wind and wind turbines will be given. At the end of this section, the concept of a wake will be introduced. In §2.3, wind farm control objectives in terms of performance indicators will be presented. Typically, controllers are designed and evaluated according to these indicators. In §2.4, control-oriented wind farm modeling will be discussed. These models can be used for designing and/or testing a controller. In §2.5, control of wind farms will be introduced and typical wind farm sensors and actuators will be discussed. In §2.6, a categorization of wind farm control strategies will be presented. In §2.7, a number of field tests for model validation are briefly discussed. In §2.8, conclusions and an outlook will be provided.

2.2. WIND AND WIND TURBINES

This section briefly introduces wind energy and single wind turbine control as it pertains to the challenge of larger wind farm control. A more complete and detailed description can be found in (Burton et al., 2001; Bianchi et al., 2007; Tong, 2010; Hansen, 2015). This section will end by introducing the concept of a wake and its essential characteristics relevant for wind farm control-oriented modeling and control.

2.2.1. WIND

Wind is the source of energy exploited by a wind turbine. Wind flows are mainly caused by the Earth's rotation and thermal heating of the Earth's surface by the sun, hence wind is ubiquitous. However, its force is not everywhere equivalent. The behavior of wind at a specific location and for a certain time instant can be characterized by a direction and magnitude. The process of energy extraction by turbine rotors can better be understood by looking at the energy extracted from the wind flowing through a thin disk (see Fig. 2.1), with this disk being equivalent to the rotor swept area.

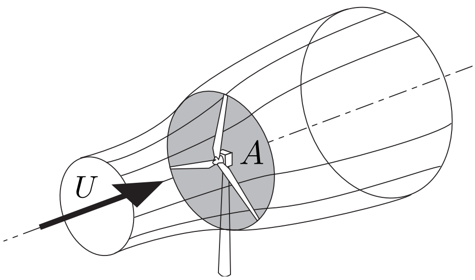

Figure 2.1: Flow with velocity U [m/s] through a rotor disk with rotor swept area A [m^2]. Figure adapted from (Burton et al., 2001).

From the continuity equation of fluid mechanics, the mass flow of air is a function of air density ρ [kg/m^3], surface area A [m^2], and flow velocity U [m/s]. Assuming the latter is uniform across the rotor swept area, A, the mass flow of air $\frac{dm}{dt}$ through a rotor disk is defined as

$$\frac{\mathrm{d}m}{\mathrm{d}t} = \rho A U. \tag{2.1}$$

The instantaneous kinetic power of the wind available at surface A, P_w [W], is calculated by

$$P_\mathrm{w} = \frac{1}{2}\frac{\mathrm{d}m}{\mathrm{d}t}U^2 = \frac{1}{2}\rho A U^3. \tag{2.2}$$

Note that the power expression depends linearly on the rotor disk area, A, (and thus rotor radius squared), and on the wind velocity, U, cubed. This implies that relatively higher gains in power generation can be achieved by placing turbines at locations with high wind velocities.

However, a wind turbine cannot extract all this available power from the wind, as the flow is required to still have velocity behind the rotor. The theoretical limit for energy extraction by a rotor is determined by the Betz limit (Betz, 1920). This limit will be, *i.a.*, discussed in the following section.

2.2.2. WIND TURBINE

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There are different types of vertical-axis and horizontal-axis wind turbines. The most commonly produced and used wind turbine is the upwind horizontal-axis wind turbine. One of its advantages can be explained by the fact that the blades are always facing fully into the wind, because incoming wind does not have to pass the turbine tower first (in contrast to downwind turbines) or other blades (in contrast to vertical-axis turbines). A horizontal-axis wind turbine consists of a rotor, most often with three rotor blades, that is attached to the generator through a drivetrain. The generator and drivetrain are housed in the nacelle, which is supported by a tower. See Fig. 2.2 for a schematic representation of the main wind turbine components.

The rotor blades convert the momentum of a wind field passing the rotor plane into aerodynamic forces that drive the rotor. The drivetrain transfers the aerodynamic torque from the rotor to the generator shaft, either directly (direct drive) or through a transmission (gearbox). The generator converts rotational kinetic power into electrical power by generating a reactive torque on the shaft. To control the power production and forces (torques) on the wind turbine, a number of degrees of freedom (control variables) are typically available:

- Blade pitch (θ) - The rotor blades can rotate, with their axis of rotation aligned with the blades, using hydraulic actuators or servo pitch motors. Pitch control can be used to influence the power capture (see, *e.g.*, (Hand and Balas, 2002)) and the loads (see, *e.g.*, (Bossanyi, 2003, 2005; Selvam et al., 2009; Ungurán and Kühn, 2016)) experienced by the wind turbine.
- Generator torque (τ_g) - The generator converts mechanical power into electricity. Torque control is used to control the power capture.
- Yaw (γ) - The nacelle can rotate, with the axis of rotation aligned with the tower, using a yaw motor. The yaw angle is defined as the angle between the axial rotor axis and the incoming wind direction. In single turbine control, yaw control is

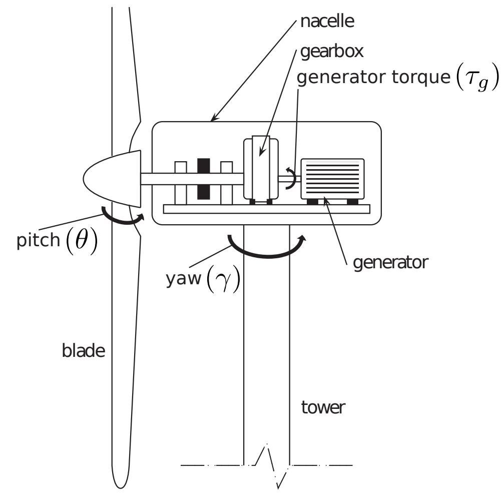

Figure 2.2: Horizontal-axis wind turbine with labeled main components and control variables. Figure adapted from (Bianchi et al., 2007).

often used to set the rotor plane perpendicular to the incoming wind direction to increase the turbine's power capture.

The control variables are shown in Fig. 2.2 with a number of basic components of a wind turbine. With these control variables we can optimize the performance of a single wind turbine, such as produced power, P, and turbine loading. An uncommon, and for now more scientifically interesting, control variable is the tilt angle of a turbine. This is defined as the difference of the wind angle of attack and the nacelle angle, with respect to the horizontal plane. In current wind turbines, this tilt angle is fixed.

A wind turbine exerts a force on the wind flowing through the rotor. This thrust force represents the amount of energy extracted from the flow and can be described by

$$F = C_T(\theta, \lambda, \gamma)\frac{1}{2}\rho A U_\infty^2 , \tag{2.3}$$

with U_∞ [m/s] as the free-stream wind velocity and $C_T(\theta,\lambda,\gamma)$ as the dimensionless thrust force coefficient, which is a function of the tip-speed ratio, λ, blade pitch, θ, and yaw angle, γ. The tip-speed ratio is defined as the ratio of the tangential speed at the blade tip to free-stream wind velocity:

$$\lambda = \frac{\omega R}{U_\infty}, \tag{2.4}$$

with R the rotor radius and ω the rotor rotational speed. The tip-speed ratio is directly influenced by the rotor speed, which is influenced by the generator torque or by changing the pitch angle to change the lift forces on the rotor blades. The generator torque control loop is relatively fast because the system is manipulated at the electrical level, though changes in the rotor speed itself are not that fast due to inertia, especially for large rotors. Although the blade pitch control loop is slower than the torque loop, it is still relatively fast because of powerful motors that typically can achieve up to a 10 [deg/s] blade pitch rate for a utility-scale wind turbine.

The power in the wind across a rotor was given in (2.2). Although power production can be improved using control, not all the power in the wind can be extracted by a wind turbine. The wind power available for extraction by a turbine is given by:

$$P = C_P(\theta, \lambda, \gamma)\frac{1}{2}\rho A U_\infty^3\,, \tag{2.5}$$

where $C_P(\theta, \lambda, \gamma) < 1$ is the dimensionless power coefficient and the ratio of generated power by the wind turbine to the available power in the wind (see (2.2) and (2.5)). There are many models in literature that provide expressions for the thrust and power coefficient. One popular way to get an expression for the force and power coefficients is by exploiting the momentum theory developed in the 19th century by W. J. M. Rankine, A. G. Greenhill, and R. E. Froude. R. E. Froude, D. W. Taylor, and S. Drzewiecki combined momentum theory with blade element theory, which resulted in the blade element model (BEM) for calculating the forces that a blade exerts on a flow. When these forces are then converted into a disk of distributed forces that model the rotor, this is referred to as the actuator disk model (ADM). In (Burton et al., 2001), it is explained that, by using momentum theory for an ideal rotor, the thrust coefficient, C_T, and power coefficient, C_P, can be written as:

$$C_T(a, \gamma) = 4a(\cos(\gamma) - a), \quad C_P(a, \gamma) = 4a(\cos(\gamma) - a)^2, \tag{2.6}$$

for $0 \le a \le \frac{1}{2}$ and the yaw angle, γ. The parameter, a, is called the axial induction factor of a wind turbine. It is the ratio of the difference between U_∞ and the wind velocity at the rotor U_r to U_∞, and is defined as:

$$a = \frac{U_\infty - U_r}{U_\infty}. \tag{2.7}$$

The axial induction factor is thus a measure of the decrease in wind velocity behind a wind turbine and provides a relatively simple expression for coordinated control of wind turbines. Note that this factor, or more precisely, U_r, can be controlled using the generator torque and blade pitch angle, but is also influenced by the yaw angle.

It was already stated that even a perfect wind turbine cannot fully capture all of the available power in the wind. There is a theoretical maximum that can be extracted by a turbine. This maximum can be obtained by calculating the supremum of $C_P(a, \gamma)$, given in (2.6), as a function of the axial induction factor and yaw angle. It can be found that for any wind turbine, the induction factor that results in the maximum power extraction is $a^\star = \cos(\gamma)/3$, which translates to a theoretical limit of $C_{P_{\max}} = 16/27\cos^3(\gamma)$, which is approximately 0.6 if $\gamma = 0$. This theoretical maximum is called the Betz limit. In a practical sense, the maximum power coefficient for horizontal-axis wind turbines lies around 0.45 according to (Bianchi et al., 2007). The maximum force can be found in a similar way: for $a = 1/2$, the wind exerts the maximum force on the wind turbine. Note that empirical data published in (Marshall and Buhl, 2005) revealed that the thrust coefficient expression given in (2.6) is not accurate when $a > 1/2$. A possible correction based on empirical data has been proposed in that paper. This correction is based on the Glauert empirical relation between the thrust coefficient and axial induction.

A more detailed representation of the rotor than the ADM is the actuator line model (ALM), which represents each blade individually in the flow, as a distribution of forces along a rotating line.

OPERATING REGIONS

For single wind turbines, different operating regions can be distinguished. Each region has its own control strategy and is typically determined based on a generator speed feedback signal. The ideal power curve for a variable pitch/speed wind turbine is shown in Fig. 2.3. In addition, a wind power curve is depicted and the ratio between this curve and

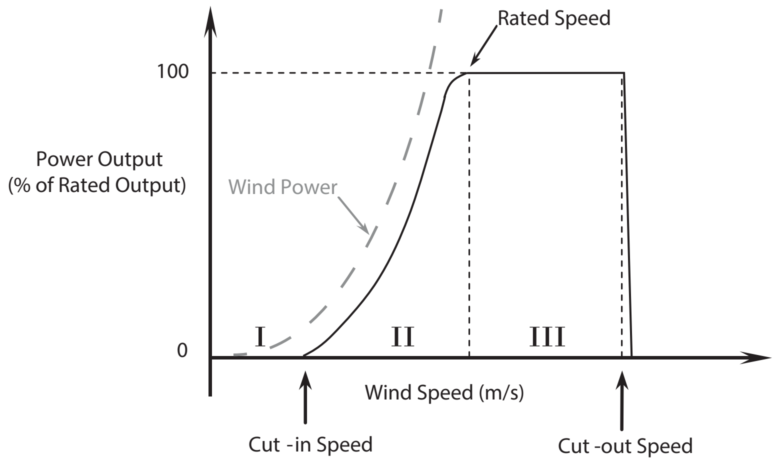

Figure 2.3: Typical wind turbine power curve. Figure adapted from (Tong, 2010).

the power curve is defined by the power coefficient. The ideal power curve exhibits three main regions with distinct control objectives. In Region II, the control problem can be seen as a tracking problem, whereas in Region III, the control problem can be seen as a disturbance rejection problem.

2.2.3. WAKE

As a wind turbine extracts energy from the wind, it causes a change in the wind flow downstream from the wind turbine. The altered flow is called the wake of a turbine. The wake characteristics are space-, time-, and parameter-dependent. A wake is space-dependent because, e.g., far downstream of a turbine, it is different from the wake closer downstream of the turbine. The wake is also time-dependent because the operation of a wind turbine changes over time as well as the surrounding flow. Finally, a wake is parameter-dependent, as the external variables (such as temperature) influence the behavior of the wake. It should be clear that studying and modeling a wake is a broad research topic by itself and ongoing (Sanderse et al., 2011; Bartl and Sætran, 2016). Models range from low to high fidelity, where the latter describes the wake in more detail and tries to capture more of its characteristics than the former. However, this increase in precision will result in higher computational costs. A more complete discussion on different wake models is presented in § 2.4.

Typical characteristics of a wake and its main causes are:

- Wind velocity deficit, as a result of the turbine's energy extraction.
- Increased turbulence intensity, as a result of *i.a.*, the turbine blade's rotation.
- Wake recovery, which is the phenomenon that downwind a wind turbine, *i.a.*, the wind velocity recovers to the free-stream velocity due to mixing.
- Wake meandering, which is a large-scale stochastic phenomenon of a wake in which the entire wake structure will show horizontal and vertical oscillations over time, rather than maintaining a certain fixed position and shape (España et al., 2011; Medici and Alfredsson, 2006).
- Wake expansion, which occurs with distance from the turbine and can be explained using the law of mass conservation and the assumption of flow incompressibility. It can be shown that a decrease in velocity means a proportional increase in the wake's cross-sectional area (see *e.g.*, (Hansen, 2015)).
- Wake deflection, which is the phenomenon that the complete wake is diverging in the latitudinal direction from the rotor center because of blade rotations (Fleming et al., 2014a) or the fact that the rotor is not oriented perpendicular with respect to the incoming wind, *i.e.*, a yawed or tilted turbine.
- Wake skewing, as a result of veer (Gebraad et al., 2016a).
- Vertical wind shear, which is the change of wake properties with height, typically an increase of wind speed with height because of ground friction.
- A kidney-shaped wake, as a result of a yawed turbine (Howland et al., 2016).
- Wake rotation due to the rotating turbine blades.

Note that the external atmospheric properties also have a critical impact on wakes and their propagation, and thus, *i.e.*, land-based and offshore wind turbines develop different wakes. Fig. 2.4 illustrates a horizontal slice of the wake at turbine hub height with $\gamma = 30°$. The contour plot with normalized velocities is obtained from wind tunnel data.

Using momentum theory and assuming $\gamma = 0$, a lower bound on the wind velocity, $U\_$, and a wind velocity at the rotor, U_r, can be estimated as

$$U\_ = U_\infty(1-2a), \quad U_r = U_\infty(1-a). \tag{2.8}$$

As stated before, it is through the wake that an upwind turbine can influence the performance of downwind turbines. The key objective of wind farm modeling and control is to take these interactions into account and use control variables to ensure a specific level

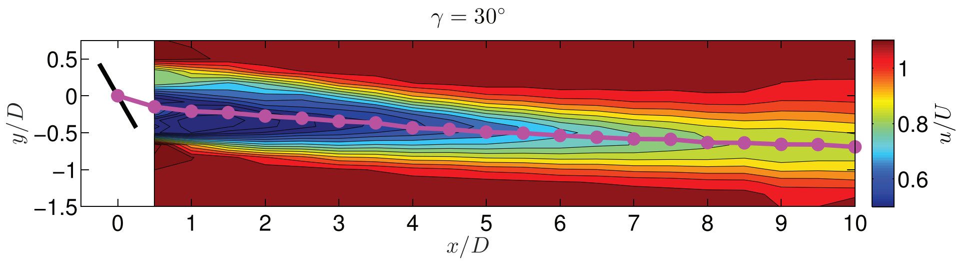

Figure 2.4: A time-averaged, stream-wise wind velocity contour plot at hub height obtained from wind tunnel data. The center of the wake is shown in filled magenta circles. Figure taken from (Howland et al., 2016).

of performance. One option is to capture the nonlinear stochastic behavior in a mathematical model and then use this model to design a controller that guarantees a performance. The assumption is that, when applying this controller to the real wind farm, equivalent performance will be achieved as predicted by the model used for controller design. This assumption is based on the validity of the used model. In this approach lies one of the main challenges in wind farm modeling and control: understanding wake behavior and capturing the important dynamics of wake interactions. An open question is: which wake dynamics are important for a control-oriented wind farm model. A subsequent challenge is controller design for the identified model. Most standard controller synthesis methods known in literature are based on linear state-space models. When dealing with nonlinear and stochastic systems, control design techniques are less available, and optimal performance can (in these cases) not be ensured because of possible local minima.

Another option is to find an optimal control policy following a model-free approach. Both model-based and model-free approaches will be discussed later in this chapter. In §2.3, an introduction to wind farms will be given. This chapter will then discuss control-oriented modeling and control of a wind farm in §2.4 and §2.5, respectively.

2.3. WIND FARM: MOTIVATION AND CHALLENGES

The previous section gave a brief introduction on wind energy and single turbine control and ended by introducing the concept of a wake. This was defined as the changed downstream flow caused by a wind turbine (see Fig. 1.3) and can result in interactions between wind turbines. It was stated that wind farm control aims to take these interactions into account while ensuring wind farm performance. This section follows by discussing reasons why it is interesting to study wind farms, and also the related challenges.

Placing turbines together has a number of benefits, which are, *i.a.*:

- Reduced deployment costs of the turbines.
- Reduced deployment costs of the electricity grid.
- Reduced operation and maintenance costs.

Especially in densely populated countries such as the Netherlands, deploying turbines

Figure 2.5: Part of the Gemini offshore wind farm located in the Netherlands. Picture taken from `http://geminiwindpark.nl/foto-s.html`.

individually is unfeasible, with governments often investing in both land-based and offshore wind farms. However, grouping turbines together in farms also introduces a number of complications that often significantly affect their performance. These complications can impact downstream turbines as follows:

- Because of the wind velocity deficit in the wakes of upstream turbines, the downstream turbine will capture less power than when operated in free-stream conditions (Steinbuch et al., 1988; Johnson and Thomas, 2009).
- As a result of increased turbulence in the wake, fatigue loads on the downstream turbine can increase (see, *e.g.*, (Hahm and Wußow, 2006; Bossuyt et al., 2017)), thereby shortening its lifetime in the absence of control algorithms that take this turbulence increase into account.
- In most cases, the center of the wake will not coincide with the center of a downstream rotor. This can be caused by wake meandering, deflection, and wind direction (mostly). Because of this, there is more thrust on one side of the rotor, leading to large cyclic variations as the blades pass in and out of the wake (van Dijk et al., 2017; Zalkind and Pao, 2016). This imbalance can contribute to an accelerated structural degradation of waked turbines.

Wind farm control consists of finding control inputs using measurements to increase the performance of a wind farm, thus improving quality or minimizing the cost of wind energy. The latter can of course be carried out by increasing the spacing between turbines, though this may have a negative impact on the aforementioned advantages, such as reduced deployment costs of the electricity grid. Also, obtaining the required spacing is an increasing challenge as rotor sizes grow with the newer turbines. Next, the objectives and corresponding challenges in wind farm control will be discussed.

2.3.1. OBJECTIVES OF WIND FARM CONTROL

In this section, the two most common wind farm performance indicators will be discussed. In general, the goal of wind farm control is to minimize the cost of wind energy. This can be translated into a number of technical objectives, namely maximizing power production, minimizing structural degradation, and active power control (APC). APC provides grid services, such as frequency control and power reference tracking, and its objective is to improve the quality of wind energy. It will not be discussed in this chapter, though interested readers can find related information in (Aho et al., 2012; Ela et al., 2014; Fleming et al., 2016a; Göçmen et al., 2016a; van Wingerden et al., 2017; Shapiro et al., 2017a; Vali et al., 2018b; Boersma et al., 2018a) and Chapter 4. The power production and load performance indicators will be discussed in this section.

POWER PRODUCTION MAXIMIZATION

Wind turbines extract momentum from the flow, which results in the previously explained velocity deficit in the wake. The amount of this deficit limits the power production of downwind turbines, but can be controlled using the wind farm control variables that will be discussed in §2.5.1. In (Fletcher and Brown, 2010), the authors show that, when considering a perfectly aligned two-turbine case, the power loss of the downwind turbine scales approximately linearly with the spacing. Losses range from around 25% for radially aligned turbines spaced 16 rotor diameters apart to 80% when the aligned turbines are placed 4 rotor diameters apart. The study in (Barthelmie et al., 2009) reports a power production loss of 12%, averaged over different wind directions, in an offshore wind farm as a result of wake effects.

It is important to note that results like these are in general obtained using a specific mathematical model trying to capture the wake dynamics for specific atmospheric conditions. Outcomes can differ according to the model and method used. However, wake loss predictions have also been measured in real wind farms. Wind farm control can mitigate part of the wake losses, although given the variable nature of a wake, it is still a point of research to quantify how much wind farm control can reduce wake losses exactly.

LOAD MINIMIZATION

A wind turbine structure has been designed to withstand steady loads several times larger than nominal loads (Spudic et al., 2010), and so it is necessary to study fatigue loading with respect to the lifetime of a wind turbine. In (Sutherland and Herbert, 1999), it is stated that modern wind turbines are fatigue-critical machines, *i.e.*, the design of many of their components is dictated by fatigue considerations. The authors in (Soleimanzadeh et al., 2012) also conclude that mostly dynamic loads are responsible for fatigue and reduced lifetime of wind turbines in wind farms. In these papers, different loading models were used, hence it is important to first investigate which type of loading occurs. The three most important sources for the loading of an upwind horizontal-axis wind turbine are (Hansen, 2015):

- Gravitational loading.
- Inertial loading.
- Aerodynamical loading.

The first type of loading is caused by the gravitational field of the Earth and rotation of the blades. It is clear that a blade rotating downward experiences different forces than a blade rotating upward. It causes a sinusoidal loading on the blades with a frequency corresponding to the rotor rotation of once per revolution (1P). Inertial loading occurs when the wind turbine changes the rotation speed. Certain parts on the blades experience different changes that will result in inertial loading. Another source is the centrifugal force acting on the blades. Aerodynamical loading is caused by the flow passing the wind turbine and varies in space and time. For example, a wind field contains a velocity profile with a bigger magnitude that is relatively high from the ground because of shear effects, whereas the turbulent effects introduce time-varying behaviour in a wind field. Also, according to (Hansen, 2015), the yaw (and tilt) angle of a wind turbine causes additional aerodynamical periodical forces on a wind turbine. In a wind farm, a wind field will also be perturbed by wind turbines causing changes in a wind field as highlighted at the end of §2.2. Downwind turbines in a wind farm can then experience a changing wind field over the rotor that can introduce additional aerodynamical loading. Loading can, in the end, lead to fatigue damage and breakdowns. There are different measures of fatigue loading, such as the rainflow counting, spectral, stochastic, and hysteresis operator method. This chapter does not cover these methods, but the interested reader is referred to (Berglind and Wisniewski, 2014).

The purpose of single turbine control is to mitigate the effects of gravitational, inertial, and aerodynamical loading. On a wind farm control level, it is more important to focus on the effects of the changed aerodynamical loading caused by the upwind wind turbines in the farm. Damage equivalent load (DEL) is a measure that is commonly used in literature to quantify loading, and allows for direct quantitative comparisons of different loading types on the turbine structure. DEL defines the equivalent fatigue damage caused by a load, taking into account the fatigue properties of the material.

In this section, two wind farm performance indicators were introduced. Wind farm control aims to optimize these indicators. For synthesis and evaluation of controllers, wind farm models are typically used. This will therefore be the topic of the following section.

2.4. CONTROL-ORIENTED WIND FARM MODELING

The advancements in wind farm control have gone hand in hand with advancements in wind farm modeling, as typically modern control algorithms rely on an internal model. These models are often simple and relatively computationally inexpensive. We refer to these types of models as low fidelity (possibly parametric) models. High fidelity simulation models are typically used to assess a controller's performance as the last step before being put to the test on an actual wind farm. These models are more accurate, but also significantly more computationally time consuming, and can therefore not be employed for real-time control. Although wind farm models are different, two main components can always be distinguished:

- Turbine model: These models predict the interaction between the flow and the turbine structure. Additionally, structural loads on the turbine given the incoming flow field may be predicted, which can include extreme loading, vibrational modes, and fatigue.
- Flow model: A model that predicts the flow properties in a wake or of the total flow field in a wind farm.

A turbine model gets a flow field from a flow model as an input, whereas the turbine loadings are inputs to a flow model that indicates the unavoidable interconnection between the two submodels. The two types are described next.

2.4.1. TURBINE MODEL

Wind turbine models describe the flow effect on the turbine structure, including loading and vibrations. A flow field serves as an input with which the turbine model evaluates the resulting loading. Two models traditionally used for estimating aerodynamic loading are the ADM and ALM, both introduced in §2.2. These models can predict turbine flow interactions and provide estimations of the turbine's power capture and forces exerted on the flow. A more elaborate turbine model is FAST (Jonkman and Buhl, 2005), developed by the National Renewable Energy Laboratory (NREL). It contains, *i.a.*, the ALM and takes into account, given an incoming flow field, all of the three types of loading discussed in §2.3.1. DEL values can be determined and the lifetime of a turbine can be assessed. Other turbine models exist, such as HAWC (Larsen et al., 2012), but will not be further discussed in this chapter. By using models such as these, accurate predictions can be made on the (extreme and fatigue) forces, moments, and vibrations of a turbine structure for given wind conditions. Also, these models provide accurate predictions of power capture of the turbine at given inflow conditions. It should be clear that more advanced turbine models require relatively more computation time. An overview of the components generally present in such turbine models can be found in (Moriarty and Butterfield, 2009).

2.4.2. FLOW MODEL

It was previously stated that the dynamical behaviour of a wake (or more general, a flow) is governed by the three-dimensional (3-D) unsteady Navier-Stokes equations. These equations are mathematically defined as a nonlinear infinite dimensional system with equality constraint. Under boundary conditions (inflow conditions) and forcing terms (the wind turbines) typically used in a wind farm model, and without making significant assumptions, no analytic solution has been found yet for these equations. Hence, in such a case, it is impossible to solve the governing equations directly. Computational fluid dynamics (CFD) is a branch of fluid mechanics that uses numerical analysis and algorithms to solve and analyze this type of problem.

Spatial discretization is a method that is applied to obtain a set of solvable equations. Because turbulence exists on many different temporal and spatial scales in a wind farm, the most accurate way to simulate turbulent flows is to directly solve the obtained set of equations on a very dense grid, capturing all eddy scales. This method is referred to as direct numerical simulation (DNS). It is computationally expensive because, after spatially discretizing, the dimensionality of the obtained set of equations is huge as a result of the fact that every cell in the wind farm has its own Navier-Stokes equations. Large-eddy simulations (LES), on the other hand, resolve the governing equations (after spatially or temporally filtering the Navier-Stokes equations) on a coarser mesh (capturing only the large-scale eddies), but can approximate the smaller-scale eddies with subgrid models. Small-scale turbulence is then calculated within each coarse cell using this subgrid model. Most wind farm flow solvers that are considered as high fidelity models employ this method.

Less computationally expensive models are also present in literature. Most of these models consider a two-dimensional (2-D) space to reduce the model complexity and assume incompressibility of the flow, and only have a simplified turbulence model to induce wake recovery. In addition, parametric models exist that only estimate specific characteristics of a wake, such as velocity deficit and wake deflection. This chapter will continue giving a brief overview of some wind farm models that exist.

2.4.3. EXAMPLES

Wind farm models that use LES flow models include Simulator fOr Wind Farm Applications (SOWFA) (Churchfield et al., 2012) and UTD Wind Farm (UTDWF) (Martinez-Tossas et al., 2014), a wind farm model developed at UT Dallas, and SP-Wind (Leuven) (Meyers and Meneveau, 2010), and PArallelized LES Model (PALM) (Maronga et al., 2015). These 3-D, high fidelity flow solvers contain, in general, sophisticated wind turbine models and 10^6 or more states. The resulting computation time can be on the order of days or weeks using distributed computation. It should be clear that these types of models are not useful for online control, wherein measurements are fed into a controller that calculates optimal actuator settings based on an internal model in real time. However, these models can serve as analysis tools. The cost of doing simulation experiments using these solvers is significantly less than the cost of doing experiments on a real wind farm. Moreover, simulation experiments can be done in controlled atmospheric conditions, which is important for one-to-one quantitative comparisons after, *e.g.*, changing a control policy.

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The authors in (Soleimanzadeh et al., 2014; Boersma et al., 2016b, 2018b) present more control-oriented and relatively less computationally expensive wind farm models based on the unsteady 2-D Navier-Stokes equations following a LES approach. It is attempted to solve the set of discretized equations governing the wake and wind turbines directly, without model reduction nor any assumptions other than incompressibility. The number of states in these models can easily be 10^3 or more, which makes it challenging to use them for controller design. A second challenge using this approach is the choice of a (relatively simple) turbulence model, which should be included to account for wake recovery. In (Boersma et al., 2018b), the authors include a simplified mixing-length turbulence model to create wake recovery behind a turbine, whereas in (Soleimanzadeh et al., 2014), no turbulence model is included. In these dynamic wind farm models, the turbines are modeled using the ADM. The cost of solving these wind farm models is relatively low because of the exploitation of sparsity and structure in the system's matrices.

Another approach is using simplified versions of the governing equations. For example, in the 2-D Ainslie (Ainslie, 1988) and 2-D dynamic wake meandering (DWM) model (also called the Larsen model) (Larsen et al., 2007), assumptions are made such that the Navier-Stokes equations can be approximated with a thin shear layer approximation that is less computationally expensive. Currently, NREL is developing FAST.Farm, which extends the DWM model to include more control-relevant dynamics (Jonkman et al., 2017). WakeFarm (also referred to as Farmflow), developed at Energy research Centre of the Netherlands (ECN), simulates the wind turbine wakes by solving the steady parabolized

Navier-Stokes equations in perturbation form in three dimensions (Crespo et al., 1988; Özdemir et al., 2013). When applying time averaging on the Navier-Stokes equations, the Reynolds Averaged Navier-Stokes (RANS) equations can be obtained. With this approach used in, *e.g.*, (Annoni and Seiler, 2015), a time-averaged (mean) flow is computed and the effects of turbulence are implemented using the mixing-length hypothesis. The computational cost for using RANS equations in a wind farm model will also be computationally less expensive than for high fidelity flow solvers. A combination is presented in (Iungo et al., 2015b), in which the authors present a RANS wind farm model for which model parameters are updated online using the high fidelity flow solver UTDWF. The authors in (Bastankhah and Porté-Agel, 2016) present a, with wind tunnel experiment data validated, wind farm model based on simplified RANS equations. The simplification results in the approximate governing equations upon which an inexpensive analytical model is built. A completely different dynamic wind farm model is presented in (Rott et al., 2017) where the Navier-Stokes equations are solved using a semi-Lagrangian approach. The interested reader is referred to (Mcdonough, 2004; Blazek, 2001) for more background information on the Navier-Stokes equations and its varieties.

One way to circumvent the complexity of wake modeling is by using 2-D parametric models. The idea is to capture only the most dominant wake characteristics. Most of these parametric wake models estimate a steady-state situation for, *i.a.*, a given inflow direction. If the wind farm is large, this inflow direction should then hold for the whole farm, which can be an unrealistic assumption. Examples are the Frandsen model (Frandsen et al., 2006), the model presented in (Porté-Agel and Niayifar, 2016), and the Jensen Park model (Jensen, 1983; Katic et al., 1986), which predict a linearly expanding wake with a velocity deficit that only depends on the distance behind the rotor. Extending Jensen's model resulted in the parametric model called FLOw Redirection and Induction in Steady-state (FLORIS) (Gebraad et al., 2014). A dynamical version named FLOw Redirection and Induction Dynamics (FLORIDyn) of this is presented in (Gebraad and van Wingerden, 2014) and a similar model is SimWindFarm (Grunnet et al., 2010), wherein relatively simple dynamical equations are used to estimate the velocity deficit in a wake. Interestingly, recent findings have shown that these simple parametric models, such as the Jensen model and models based on the Jensen model like FLORIS, can in some cases predict wake losses accurately, if uncertainty is included in the calculation (Rostampour et al., 2013; Gaumond et al., 2014; Peña et al., 2015). Inclusion of uncertainty in wake models, and evaluating controllers based on uncertain wake models, is an active field of research.

Note that never all flow behaviour will be captured when simulating a wind farm using a model, especially when employing a 2-D model. For example, in the latter case, the inflow from above and below is not taken into account, even though it influences wake properties. In addition, the underlying assumption of infinitely tall turbines in 2-D models that are based on the unsteady Navier-Stokes equations results in flow speedup effects on the right and left downwind the turbines. Interestingly, the model presented in (Boersma et al., 2017) includes information on the third dimension in the 2-D unsteady Navier-Stokes equations, effectively reducing this undesired effect. However, for some specific cases, 2-D wind farm models have been validated with high fidelity 3-D models, which hints to the fact that the assumption could be reasonable. It is the time-reducing property that makes 2-D models attractive for wind farm control.

In addition to the above, the authors in (Sanderse et al., 2011; Sanderse, 2009; Crespo et al., 1999; Vermeer et al., 2003; Göçmen et al., 2016b; Annoni et al., 2014) provide overviews of rotor blade models and wake models. In Table 2.1, a classification of previously described models is given, noting that in this table the term "fidelity" is mainly used to describe the amount of detail described by the model. This does not automatically imply that more detailed models are more suitable for (online) control purposes, as discussed before. In addition, it has been shown in several wind farm simulation cases that medium and low fidelity models are able to estimate wind velocity and power data from a high fidelity model. The acronym NS stands for the Navier-Stokes equations.

Table 2.1: A classification and properties of different models.

<table>
<tr><th></th><th colspan="2">Low fidelity</th><th>Medium fidelity</th><th>High fidelity</th></tr>
<tr><td>Model type</td><td colspan="2">Kinematic models</td><td>Flow field models</td><td>Flow field models</td></tr>
<tr><td>Fundamentals</td><td colspan="2">Parametric</td><td>2D NS</td><td>3D NS</td></tr>
<tr><td>Models</td><td>Jensen, FLORIS, Frandsen, ...</td><td>FLORIDyn,...</td><td>DWM, WFSim, Ainslie...</td><td>SOWFA, WakeFarm, UTDWF, SP-Wind,...</td></tr>
<tr><td>Flow dimension</td><td colspan="2">2D</td><td>2D</td><td>3D</td></tr>
<tr><td>Dynamic/Static</td><td>Static</td><td>Dynamic</td><td colspan="2">Dynamic</td></tr>
<tr><td>Turbine model</td><td colspan="2">ADM</td><td colspan="2">ADM/ALM and/or an aerodynamic package (e.g., FAST)</td></tr>
<tr><td>Comp. effort</td><td colspan="2">Order of seconds on a desktop PC</td><td>Order of minutes on a desktop PC</td><td>Order of days on a cluster of 10^2 CPUs</td></tr>
<tr><td>Model accuracy</td><td colspan="2">Low – medium</td><td>Medium – high</td><td>High – very high</td></tr>
</table>

REDUCED ORDER MODELS

Performing model order reduction techniques, such as proper orthogonal decomposition and dynamic mode decomposition on high fidelity flow solver data, is another method to obtain a model. The authors in (Annoni et al., 2016b; Fortes-Plaza et al., 2018) illustrate that it is possible to apply proper orthogonal decomposition and compare the flow fields obtained with the low-order model with that of a high fidelity flow solver. Other articles that deal with proper orthogonal decomposition applied to a wind farm model are (Hamilton et al., 2015; Bastine et al., 2015). In (Hamilton et al., 2015) and (Iungo et al., 2015a), the authors illustrate that by using data from a high fidelity flow solver and dynamic mode decomposition, a low-order, two-turbine wind farm model can be obtained in which states retain a physical interpretation.

Note that model order reduction techniques rely on specific operating conditions, *i.e.*, they provide linear models for a specific operating point and are only valid within small deviation from this point. These reduced-order linear models can be defined at, *e.g.*, specific wind speeds and directions. However, techniques in parameter-varying control exist that can help link these models together (Annoni and Seiler, 2016). Also, reduced-order models could be data-driven in a more system identification approach (see *e.g.*, (Schmid, 2010)) or model-based considering, *e.g.*, the Navier-Stokes equations. Examples of the latter are balanced proper orthogonal decomposition and the Galerkin projection (see *e.g.*, (Rowley et al., 2004)). This chapter will not discuss these different techniques.

A note for this section is that a model's accuracy and applicability are highly dependent on the atmospheric conditions of the relevant wind site. It is shown in, *e.g.*, (Abkar and Porté-Agel, 2016) that wake characteristics change a lot relatively when the atmosphere is stable or not. In addition, in unstable atmospheric conditions, often wakes are extremely hard to control, and no significant improvements can be yielded by active wind farm control. In stable conditions, wakes are less difficult to control; however, the problem is still challenging.

In this section, two main components of a wind farm model were discussed and examples of wind farm models were given. These models can be used to conduct wind farm analysis or control. The latter will be the topic of the following section.

2.5. WIND FARM CONTROL

It was stated earlier that wind farm control is aimed at optimizing the previously presented objectives: minimization of power losses and structural loading. More precisely, wind farm control aims to find control actions that increase the wind farm performance by taking measurements (and possibly an internal model) into account. By (partially) relying on measurements, a controller can cope with changing environments. In this section, wind farm actuators and sensors will first be discussed, followed by the discussion of two wind farm actuation methods. The categorization of different control strategies will be covered in §2.6.

2.5.1. ACTUATORS AND SENSORS

In wind farm control, measurements from sensors and/or possibly an internal model are used to compute control settings. These control settings are assigned to the turbine's actuators, which can be considered the degrees of freedom in the wind farm control problem. In this section, typical wind farm actuators and sensors will be discussed.

ACTUATORS

For a single turbine, actuators were defined as turbine yaw, γ, generator torque, τ_g, and blade pitch angles, θ. Tilting the turbine's rotor provides an additional actuator for control, though this approach has only been used in simulations until now (Fleming et al., 2014a,b; Guntur et al., 2012; Annoni et al., 2017). In a real wind farm and some wind farm models, the control variables are $(\gamma_i, \tau_{g_i}, \theta_i)$ for $i = 1, 2, \ldots, \aleph$, with $\aleph$ the number of turbines in the farm. However, it is common in wind farm modeling to define the axial induction (see (2.7)) or similarly the thrust force coefficient (see (2.6)), and the yaw angles as actuators. Although this approach neglects the dynamics between the physical turbine actuators τ_{g_i}, θ_i and the axial induction or thrust force coefficient, it simplifies the modeling and control problem. Some studies (see *e.g.*, (Knudsen and Bak, 2013; Boersma et al., 2018c)) include a first-order time filter to circumvent sudden unrealistic axial induction changes in simulations. The following wind farm actuators can be defined for models employing the ADM:

- γ_i for $i = 1, 2, \ldots, \aleph$,
- a_i (or C_{T_i}, C'_{T_i}) for $i = 1, 2, \ldots, \aleph$.

Note that by changing a_i, the thrust force, *i.e.*, the amount of energy the turbine extracts from the flow, will change. These two variables are illustrated for one turbine in Fig. 2.6.

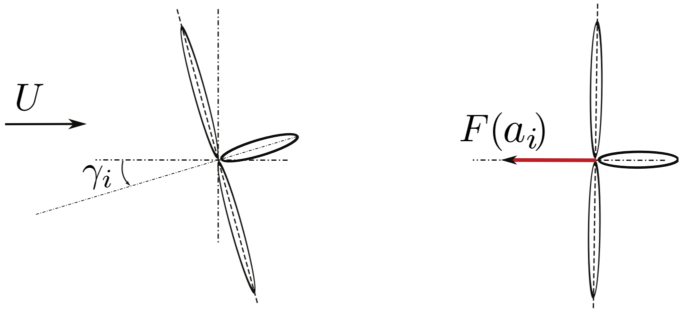

Figure 2.6: A schematic representation of wind farm actuators typically used in simulations. The thrust force, $F(a_i)$, is determined by the axial induction a_i of turbine i.

SENSORS

Proper placement and choice of sensors is key to the success of wind farm control. Examples of wind turbine sensors include:

- Anemometers and wind vanes. These devices are mounted on the nacelle to locally determine the wind speed and direction at the rotor plane. However, note that when a turbine is in operation, these measurements are disturbed because of the interactions between the flow and turbine rotor, especially at small distances around the rotor plane (Pao and Johnson, 2009).
- Power sensors.
- Strain sensors, which measure structural deformations.
- Accelerometers, which measure the turbine's acceleration.
- Generator shaft-speed sensors.
- Torque sensors.
- Temperature sensors, which are used for anti- and de-icing techniques (Parent and Ilinca, 2011).

These turbine sensors are also useful for wind farm control. Examples of sensors on a wind farm level are:

- Separate meteorological measurement masts, which are located in the farm, and provide information on the flow velocity for their respective positions.
- Remote-sensing (RS) technologies, which measure the flow field at different positions upstream or downstream of turbines, without the need for repositioning the sensor. RS can use sodar, lidar, or radar technology, or satellite scatterometry.

According to (Peña et al., 2013), sodar systems use sound waves and are deemed too slow and of too low accuracy for wind farm applications, although they are capable of wind field monitoring (Anderson et al., 2005; Barthelmie et al., 2003). More recently, lidar technology has been applied, which relies on the same principle as sodar but using laser instead of sound waves (Rettenmeier et al., 2014). The authors in (Goossens, 2015) show that sodar and lidar can achieve similar accuracy in field tests on one of the Vattenfall wind farms. However, theoretically, lidar is able to achieve higher measurement accuracy because of the nature of light (Peña et al., 2013). Furthermore, both (Rettenmeier et al., 2014; Schlipf et al., 2011a) show that lidar has real potential to improve the accuracy of current wind speed measurements above the resolution of a mast. Also, a lidar device can be placed on top of a wind turbine to measure upwind or downwind. Because a lidar device is relatively expensive, it is interesting to investigate how to use it in an optimal way such that expenses can be minimized. The authors in (Mirzaei and Mann, 2016) present such a study. Interestingly, lidar technology was initially applied for single-turbine control, incorporating feed-forward control (see, *e.g.*, (Schlipf et al., 2011a, 2013, 2014; Schlipf, 2016; Scholbrock et al., 2016; Mirzaei et al., 2013)). At this moment, radar devices are relatively expensive and large regarding dimension.

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The main challenges in RS technology are data outliers because of hard targets and interference with the turbine blades, and problematic wind field reconstruction due to the cyclops dilemma. For example, a single lidar system measures the wind from only one angle of view. Thus, with a single lidar system, it is not possible to reconstruct the full 3-D wind field without making any assumptions (Schlipf et al., 2011b). An example of this can be found in (Raach et al., 2014), which shows that it is possible to estimate a 3-D wind field using lidar.

Given the actuators and sensors, the next question is which actuation methods can be used to optimize performance within the wind farm. This will be the topic of the following section.

2.5.2. Actuation methods for wake control

Currently, most wind farms are operated using individually optimal wind turbine control settings referred to as greedy control. As stated before, wind farm control consists of finding control inputs using measurements (and possibly an internal model) to increase the performance of a wind farm, thus minimizing the cost of wind energy. It has been an active research topic since the 1990s and relies on the assumption that the performance of a wind farm can be increased by operating turbines in the farm at configurations different from their individual optimal settings. Two general control methods exist for this purpose: axial induction control (AIC) and wake redirection control (WRC). Simulation studies such as (Horvat et al., 2012; Fleming et al., 2013), illustrated that both methods have a potential to increase the power production and can influence structural loading.

Another possible future method is to actively reconfigure the wind turbines in a wind farm with floating turbines. Wind farm layout optimization can be considered as initial work towards such a strategy. This will, however, not be discussed further in this chapter though the interested reader is referred to (Stevens, 2015; Fleming et al., 2015; King et al., 2016; Mittal et al., 2017). AIC and WRC will be topics of the remainder of this section.

AXIAL INDUCTION CONTROL

The idea of AIC is to reduce the power production of upwind turbines by changing the axial induction so that downwind turbines can generate more. The axial induction is changed by adjusting the blade pitch angles and generator torque away from individually optimal settings. AIC is worthwhile if the reduced power production of the upwind turbines can be compensated for by the downwind turbines, and if performance of a turbine is significantly impacted by an upstream turbine through its wake, e.g., in situations with little wake recovery, dense turbine spacing, and relatively high wake-rotor overlap. Fig. 2.7 illustrates an aligned two-turbine situation in which this is not completely the case.

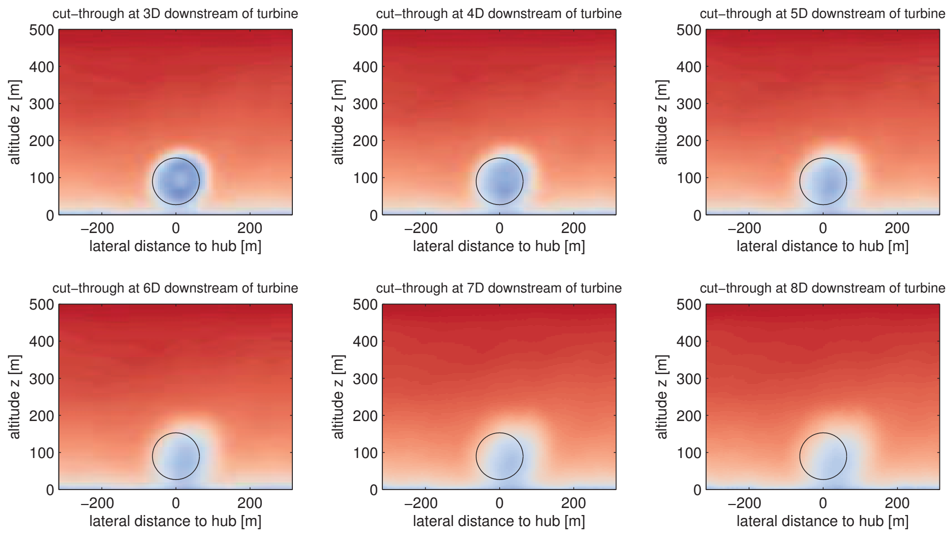

Figure 2.7: A cut-through at different distances of a wake from SOWFA data (red colored area contains higher wind velocity than the blue colored area). Figure taken from (Gebraad, 2014). It can be seen that more downwind, the wake is less overlapping the virtual downwind rotor.

Typically, in a wind farm, the distance between up and downwind turbines is around $7D$, meaning seven times the rotor diameter. Hence, the power that is purposely not captured by the upwind turbine will not be captured completely by the downwind turbines for the case in Fig. 2.7. It is the deviation of the upwind turbine wake which, according to the authors in (Annoni et al., 2016a), is, *i.a.*, determined by:

- Wind direction.

- Relative position of turbines.
- Wake meandering.
- Atmospheric conditions.
- Wake expansion.

Wind direction is important in two ways. First, changes in the wind direction in the farm contribute to deflection and skewing of the wake, which causes the wake to overlap less with the downwind rotor. Second, the wind direction is never exactly perpendicular to the rotor, and hence there will always be a deviation of the upwind turbine wake from the downwind rotor. Note that especially the latter could be captured using uncertainties in the model. Importance of wake expansion is emphasized because the authors in (Annoni et al., 2016a) show that, when using pitch offsets, most power passed by the upwind turbine is located in the outer ring of the wake. This complicates AIC, as it becomes more difficult for the downstream to capture this energy because of wake expansion. Note that this specific spatial distribution of the power cannot be modeled using the standard ADM, but can be captured using ALM.

Another interesting point regarding AIC is that, when the thrust force is reduced, the turbulent wake mixing and thereby wake recovery will be reduced. There are thus two counteracting effects: increased velocity in the near wake, but reduced recovery downstream (effectively decreasing velocity of the far wake). In (Annoni et al., 2016a), it is shown that including this effect in an engineering model reduces the expected power production increase from AIC.

Research of AIC is done quite extensively, showing inconclusive results on its feasibility. Most work in recent literature only takes power production into account, whereas loading is neglected. An example is the LES simulation results presented in (Goit and Meyers, 2015), wherein power production is increased using AIC by enforcing quick variations in the thrust force. These variations will increase turbulence in the wake and mixing with the upper boundary layer containing a higher flow velocity, which is beneficial for the power production. Subsequent work (Munters and Meyers, 2016, 2017) shows that by constraining thrust force variations, the power gain will again be reduced. Theoretically, it can be possible to increase power, but of course quick variation of thrust force will have implications on loads and these should be taken into account. Differentiation of the results can be made with respect to the used models: steady-state (Horvat et al., 2012; Mirzaei et al., 2015; Gebraad and Wingerden, 2015; Marden et al., 2013) or dynamical (Goit and Meyers, 2015; Schepers and van der Pijl, 2007; Vali et al., 2018a). In general, early results based on relatively simple steady-state parametric models illustrate increases in wind farm power production. The simplified models in mentioned studies might not represent the relevant wake phenomena in AIC, and thus it is questionable if the optimized control settings would work for the atmospheric conditions under consideration. High fidelity studies such as (Annoni et al., 2016a) and wind tunnel experiments such as (Campagnolo et al., 2016b) show that it is not always possible to increase power by AIC, and this can be explained by phenomena mentioned earlier. Interestingly, the authors in (Santoni et al., 2015) show that, although it seems that the power production cannot be increased, it can be interesting to employ AIC to reduce turbine loading while maintaining equivalent power production. In addition, AIC can possibly be used in APC.

It is still difficult to make conclusive statements on AIC. Perhaps a solution lies in adjusting the structural design of wind turbines in a farm according to previously described phenomena, but this is beyond the scope of this chapter. In conclusion, although the concept of AIC is promising, recent advances in wind farm modeling and wind tunnel and field tests have shown that possible production gains may be smaller and more difficult to harvest than initially expected based on static control strategies and more simplified models. Further research is needed to conclude whether it is possible to find a wind farm controller that will use AIC to reduce loads and/or increase production by dynamically adjusting pitch and torque settings to atmospheric conditions.

WAKE REDIRECTION CONTROL

In this approach, the rotor of the upstream turbine is purposely misaligned with the incoming flow to deflect the wake downstream so that it will not at all or partially overlap a downwind turbine. The deflection can be done using:

- Tilt actuation.
- Individual pitch control (IPC).
- Yaw actuation.

Tilt actuation will not be further discussed in this chapter, but the reader is referred to (Fleming et al., 2014a,b; Guntur et al., 2012; Annoni et al., 2017). In simulation studies, IPC is shown to be effective at inducing wake redirection, though this results in a large increase in loads (Fleming et al., 2014a). Fig. 2.8 depicts a schematic illustration of yaw actuation.

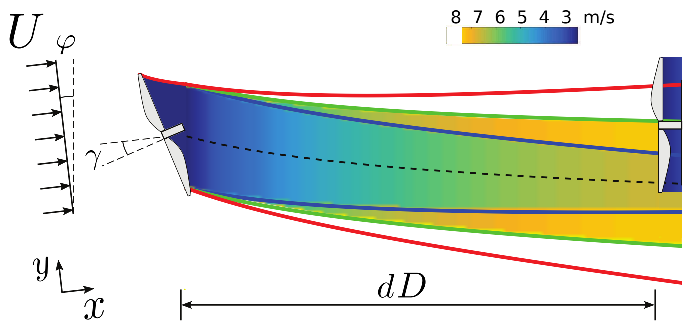

Figure 2.8: An illustration of wake redirection control with inflow angle φ and a second turbine placed d rotor diameters D downstream of the first turbine. Figure taken from (Zalkind and Pao, 2016).

Wake redirection promises significant improvements in simulation with power production increases on the order of 4%-7% (Knudsen et al., 2015) and an annual energy production increase on the order of 3%-4% (Gebraad et al., 2016b). In (Gebraad et al., 2015), a similar simulation is done as previously presented in Fig. 2.7, but instead of changing the axial induction of the first turbine, it is actuated with a yaw angle of 25 degrees. The authors conclude that the induced velocity increase caused by yaw actuation is better concentrated within the rotor area of a downwind turbine placed more than $3D$ behind the upwind turbine. Wake behavior as a result of yaw actuation is an actively researched topic (Howland et al., 2016; Vollmer et al., 2016; Bastankhah and Porté-Agel, 2016). The developments in WRC as an actuation method go hand in hand with these studies and more details regarding this method need to be investigated using simulation and field studies.

An interesting but rarely seen approach is to use both AIC and WRC (Park and Law, 2015; Munters and Meyers, 2018a). In the former, a relatively simple engineering model to capture wake dynamics is used, but its parameters are calibrated using one data set from a high fidelity flow solver. The AIC and WRC analysis is done for different wind directions. It is shown that a power increase is achieved for all studied wind directions using the proposed approach. The obtained control settings are not tested on a real wind farm nor a high fidelity flow solver. The wind farm controller presented in Munters and Meyers (2018a) provides plant wide power maximization by utilizing AIC and WRC in an adjoint based model predictive controller.

In this section, we discussed the most common wind farm actuation methods. Possible control strategies are discussed in the following section.

2.6. Wind farm control strategies

In wind farm control, a supervisory controller determines a collective control policy using measurements (and possibly an internal model) so that performance (as defined in §2.3.1) is achieved. According to this control policy, the supervisory controller assigns individual control settings as defined in §2.5.1 to each turbine in the farm. Then, relatively simple internal controllers enforce the tracking of this assigned turbine setting. In this closed-loop approach, not only the atmospheric conditions but also quantities such as power production and a turbine's structural loading can be defined as measurements. Hence, control actions can adapt to the changing wind farm and atmospheric properties, which has the potential to lead to robust control solutions. Controllers are evaluated using an internal model, which can be dynamic or static. For a dynamical model, the model states can have a physical meaning, such as wind flow velocity, but it can also be a nonvariable. No system states are present with (parametric) steady-state models.

A distinction between closed-loop controllers can be made with respect to the measurements used. In closed-loop state-feedback, all the states of the model (*e.g.*, flow velocity vectors or power signals from the turbines) are assumed to be measured and fed back to the controller. This assumption can be unrealistic, because measuring each system state can be impractical and often impossible depending on the used model. In closed-loop output feedback, only the measurements, *e.g.*, a subset of the states, are fed back to the controller and used to evaluate control actions. State estimators (observers) can be used to estimate the system states using only measurements. For example, the state of a model can contain all flow velocities (or a linear combination of these velocities) in a wind farm, whereas the output may be only the flow velocity at hub height of the rotors. An observer (discussed in § 2.6.3) can estimate all flow velocities using only these few measured flow velocities at the rotors. Different closed-loop control strategies and their applications to wind farms will be discussed next.

2.6.1. OPTIMIZATION-BASED CLOSED-LOOP CONTROL

In this strategy, wind farm measurements are fed into a controller. Here, an optimization procedure evaluates, using an internal model, optimal control inputs such as yaw angles, pitch angles, and generator torque (or axial induction) values for the turbines in the farm. In addition, the model parameters can be updated using the wind farm measurements. Then, optimal control inputs are sent to the turbines in the farm and new measurements are taken.

An algorithm that can be used for finding optimal inputs is game theory (GT). Here, favorable actions lead to high rewards and unfavorable actions to low rewards. The algorithm tries to find the most rewarding action according to the used model. The reward can, *e.g.*, be the amount of power or the experienced loading. Because of the random search actions, the algorithm needs time to converge to optimal control settings. The duration depends on the complexity of the internal model, but even if the model is a simple parametric steady-state model and consequences of certain control actions can be evaluated quickly, GT needs many iterations to converge to an optimal solution. If atmospheric conditions in a wind farm change during the search for optimal control settings, the algorithm has to start again finding optimal settings for these new atmospheric conditions. Literature such as (Marden et al., 2012, 2013) illustrate AIC using GT. For specific conditions, power production improvements are shown with respect to a baseline controller. However, relatively simple engineering wake models are used, and the found optimal inputs are not applied on a wind farm nor a high fidelity model. It is therefore not clear how these results would apply to real wind farms. The authors in (Jinkyoo Park et al., 2013) illustrate AIC and WRC using GT to optimize the power production. Using their approach on an engineering model results in improvements, though again the control settings are not tested on a more realistic situation. The authors in (Gebraad et al., 2014) apply WRC using GT with FLORIS, a steady-state model introduced in §2.4. The optimal inputs are then applied to a high fidelity model SOWFA. An increase in power with respect to a baseline controller is presented.

Another approach is extremum seeking control (ESC), an optimization approach that can work for nonlinear, time-varying systems. ESC algorithms estimate the gradient of the cost function (*e.g.*, the total power of a wind farm) using measurements. In literature such as (Johnson and Fritsch, 2012; Yang et al., 2015; Menon and Baras, 2014), AIC using ESC and a greedy controller are applied on a relatively simple wind farm model and the results are compared. The found optimal values are not sent to a high fidelity model or real wind farm to validate the results. The authors show that, for different cases, power production can increase with respect to greedy control. In (Ciri et al., 2016), AIC using ESC is applied on the high fidelity model UTDWF and power production improvements with respect to a baseline controller are presented. In (Gebraad and Wingerden, 2015), AIC using gradient-based ESC (therein defined as maximum power-point tracking (MPPT)) while having information only from neighboring turbines is applied to maximize the power output of a wind farm for different atmospheric conditions. An extended Jensen Park wind farm model is used and a benchmark power production is obtained using GT. The results illustrate that, by using gradient-based ESC, the power production can be improved with respect to the benchmark results. The optimal control inputs are not tested on a wind farm nor a high fidelity model, hence results depend on the validity of the model used. In this case study, the information for the individual wind turbines is also limited, hence a global optimum cannot be guaranteed, but the computation time is reduced. In (Campagnolo et al., 2016b), AIC and WRC using a similar gradient-based ESC algorithm as (Gebraad and Wingerden, 2015) is applied in a wind tunnel with power maximization as an objective. The case study includes three turbines with limited information for the individual turbines. Hence, again, it is observed that a global optimum cannot be guaranteed though a power production increase with respect to a baseline controller is presented. In (Park and Law, 2016), AIC and WRC using a Bayesian Ascent method is presented. Simulation and wind tunnel test results are shown for a four-turbine case. Dynamic programming is another algorithm also applied to wind farm models (see, *e.g.*, (Tang et al., 2014; Rotea, 2014; Dar et al., 2017)). The latter aims at optimizing the power production among the yaw angles employing an extended Jensen Park model. These results will not be discussed further in this chapter.

Note that the optimization-based closed-loop control results presented so far, except for (Gebraad et al., 2014; Ciri et al., 2016, 2017, 2018; Campagnolo et al., 2016b; Park and Law, 2016), are obtained using a relatively simple model. The control actions are not tested in high fidelity simulations nor a real or scaled wind farm, and the question is if similar results will be obtained when doing so. It is also important to note that GT and ESC are, in essence, model-free approaches, hence they could be applied directly on a wind farm. However, this is due to, i.a., wake traveling delays, challenging hence these methods are applied on relatively simple (fast) models. With ESC as well as MPPT, only information from neighboring turbines is used, which decreases the necessary wake traveling time. The computation time these optimization algorithms need to converge remains a critical issue because of the time-varying conditions in a wind farm, though not enough data is available to make conclusive statements on these methods. We therefore encourage researching methods that can increase the convergence rate of these optimization algorithms.

Closed-loop control based on a dynamic model has potential to find a temporally optimal solution. An example of this is presented in (Goit and Meyers, 2015; Munters and Meyers, 2016, 2018a). Here, model-predictive control is applied using the high fidelity model SP-Wind. Knowledge of all the flow velocities and wind turbine power signals is assumed and the algorithm maximizes the total power production among axial induction factors for a given time horizon. Computationally, this is a heavy task, but the results give insights into the possibilities of AIC. The authors in (Spudic et al., 2010; Soleimanzadeh et al., 2012; Vali et al., 2016) also present AIC using MPC via a medium fidelity flow model to reduce the computational effort. Power increase (and load reduction in (Spudic et al., 2010; Soleimanzadeh et al., 2012)) with respect to a baseline controller are presented, though the controller is not tested in a high fidelity model. In all the MPC examples, full state knowledge is assumed. As stated before, this is in general not realistic.

2.6.2. LINEAR DYNAMIC CLOSED-LOOP CONTROL

Examples of these approaches are PID, $\mathcal{H}_2$, and $\mathcal{H}_\infty$ controllers. These controllers are defined as dynamic controllers and can be designed using (mostly) linear models. Tracking behavior and disturbance rejection are time-domain specifications that can be imposed relatively easily on closed-loop systems.

The authors in (Soleimanzadeh et al., 2013) did implement a $\mathcal{H}_2$ controller using a medium fidelity wind farm model that neglects turbulence. The controller is tested on a nonlinear model and the authors conclude that the controller provides a distribution of power references between wind turbines so that demanded wind farm power is ensured and structural loading is minimized. The authors claim that their method can also be used to evaluate a $\mathcal{H}_\infty$ controller. Unfortunately, the controller is not evaluated on a high fidelity model.

In (Raach et al., 2016), the authors designed a PID controller for wake tracking. The controller is applied in SimWindFarm, a model discussed in §2.4. In (Raach et al., 2017a, 2018) and (Raach et al., 2017b), a $\mathcal{H}_\infty$ and a robust $\mathcal{H}_\infty$ controller are designed, respectively, to steer the wake while employing a dynamic wind farm model based on the 2-D Navier-Stokes equations. Perfect knowledge of the center of the wake using lidar is assumed in both papers. The concept of steering the wake to a certain position makes the work in these papers unique. However, the question remains as to which position the wake should be steered to increase wind farm performance as discussed in §2.3.1.

2.6.3. OBSERVER

An observer is able to estimate the full state (and possibly update model parameters) based on specific measurements. A closed-loop control scheme using an observer is depicted in Fig. 2.9.

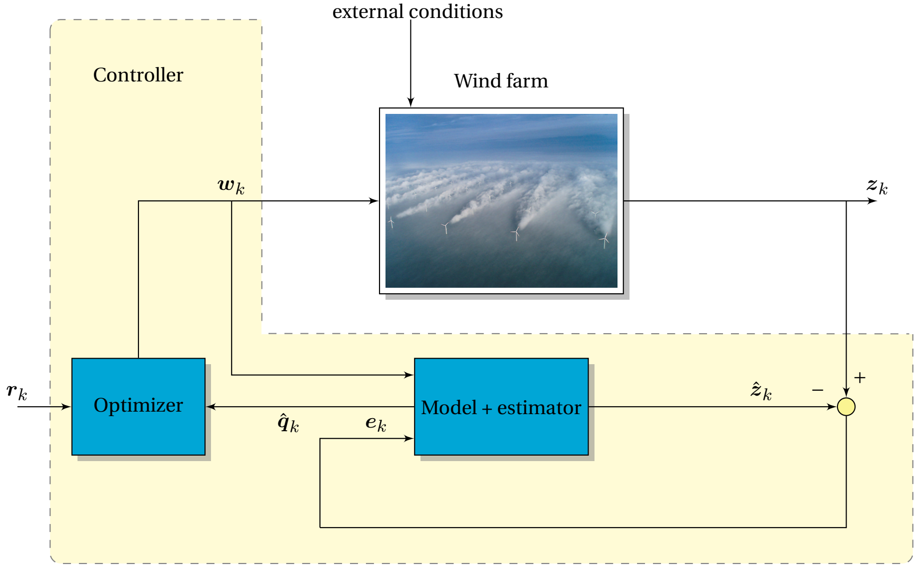

Figure 2.9: General dynamical closed-loop control framework with measurements z_k and its estimation $\hat{z}_k$ and state estimation $\hat{q}_k$. The signals r_k and w_k are reference and control signals, respectively. The observer is the model and estimator combined. Note that this figure is similar as Fig. 1.5, but repeated for completeness of this chapter.

For example, given only rotor velocities, an observer can, when containing a proper model, estimate the flow velocity vectors in the complete farm assuming observability. The latter holds true if initial conditions can be inferred from measurements (see, *e.g.*, (Åström and Murray, 2008) for more information on this topic). Observers (also called estimators) contain a dynamical model and can be used in combination with, *e.g.*, a model-predictive controller. Observer properties include the ability to:

- Estimate states from specific measurements.
- Deal with noise in measurements and may act as a low-pass filter in estimating the system states.
- Enrich the state estimation with small-scale flow behavior in which a control-oriented model is able to estimate the large-scale flow behavior.

The latter property is especially interesting because model mismatches are most likely to occur as a result of the dynamic complexity in a wind farm. In (Doekemeijer et al., 2016, 2017, 2018), the authors implement a type of observer called the Ensemble Kalman filter using a medium fidelity flow model. Although the initial results are promising in simulation with LES data, no real closed-loop simulations have yet been performed with a controller and state observer. The authors show that the flow estimations can be improved using an observer, and flow fields can better approximate high fidelity flow data when applying an observer.

In (Shapiro et al., 2016), the authors use a relatively simple dynamic wake model in an observer while taking measurements from the LESGO flow solver. The objective of the control framework is power reference tracking, and AIC using a MPC controller is applied. The results look promising. Another example of applying an observer in a wind farm simulation can be found in (Shapiro et al., 2017b).

Open questions regarding the application of an observer in wind farms are 1) what are the optimal sensor locations and 2) how many sensors should be used such that state reconstruction is still possible and qualitatively acceptable. The first question relates to increasing the information density from each sensor. Minimizing the number of sensors is from an economical perspective important. These questions are not easy to be answered due to the time-varying behaviour a wind farm exhibits.

In §2.6.1, 2.6.2 and 2.6.3, a summary of wind farm control strategies has been given. It can be concluded that most of these strategies are optimization-based and evaluate optimal control settings by optimizing a cost function. However, most controllers in literature are not implemented in a wind farm or a high fidelity flow solver to validate their true performance. Less research has been done regarding the application of modern control strategies in wind farms, thereby making this a relatively undiscovered research area. Applying observers in wind farms shows promising results, though more research is necessary.

2.7. Field tests

From §2.4, it can be concluded that there are many wind farm models that predict flow fields, power capture, and/or loading in a wind farm. Parametric and medium fidelity models are sometimes validated using flow data from high fidelity wind farm models.

However, validation of these solvers using real wind farm data is still ongoing. Although it is expensive to do field testing, it is essential for further development. Field tests are not only used to validate high fidelity flow models, but also to obtain results that show that wind farm control can be worthwhile in general. For example, field tests are described in (Barthelmie et al., 2007, 2010; Wagenaar and Schepers, 2012; Hirth et al., 2014; Fleming et al., 2016b; Sakagami et al., 2015; Fleming et al., 2017a,b). A less expensive approach is doing wind tunnel experiments (see *e.g.*, (Howland et al., 2016; Bossuyt et al., 2017; Bastankhah and Porté-Agel, 2016; Campagnolo et al., 2016b,a)). Although wind tunnel tests can provide interesting data, the experiment environment remains a scaled conditioned one. This prevents a one-to-one comparison to real wind farms. In addition, it appears to be challenging to have realistic turbines and flow characteristics at a smaller scale. However, the advantage of this is that a more idealized experiment can be performed, which can better be represented in simulation, and thus provide a better comparison between a simulation and an experiment.

2.8. CONCLUSIONS

In this chapter, basic wind farm control-oriented modeling and control concepts have been explained and literature has been categorized and discussed. The following summarizing conclusions can be drawn:

- High fidelity models are suitable for flow and wind farm controller analysis. They are also suitable for exploring the possibilities of wind farm control. However, more validation of high fidelity models with field test data is necessary to improve their quality. Because high fidelity models are computationally complex, they are not suitable for online control.
- The use of medium fidelity dynamical models can, *e.g.*, be employed to predict the available power and/or flow fields in a wind farm. In addition, they can deal with changing atmospheric conditions over space and time. However, current medium fidelity dynamical models based on the Navier-Stokes equations are still computationally complex, hence studying simple dynamical and parametric steady-state models could be helpful. The question is if a sufficient amount of dynamics can still be captured with these models so that they can be used for wind farm control resulting in realistic results. In some specific cases, medium fidelity dynamical and low fidelity steady-state models have shown similar simulation results with respect to high fidelity models, though no conclusive statement can be made yet.
- Reduced-order models can provide information on important wake farm dynamics with limited computational complexity. However, these models are valid for one specific atmospheric condition, and applicability in real wind farms is yet to be proven. Still, the use of techniques in parameter-varying control that can help link multiple linear reduced-order models is promising.
- Dynamic feedback control is a relatively open and interesting area that still can be explored in wind farm control.
- Current literature tells us that axial induction control based on steady-state models will most likely not result in power production increases without increasing struc-

tural loading. Open questions are if axial induction control can be used to minimize the turbine's structural loading while maintaining power production and if it is applicable in active power control.

- Wake redirection control is a promising actuation method for wake control. Additional field tests are required to provide more information on the true potential of this actuation method. Furthermore, it could be beneficial to study the combination of axial-induction and wake redirection control in greater detail.
- Designed controllers should be tested on real wind farms, or at least in a high fidelity wind farm simulator for different test cases, to get a better idea of their effectiveness in realistic wind farm scenarios.
- Remote-sensing technologies, or other measurement devices used in wind farms, should be researched further. These methods are critical for control algorithms to obtain reliable measurements of wake dynamics used for determining a certain control policy and to update an internal model.
- The application of an observer including model parameter estimation in a wind farm is promising. It provides the ability to take a few measurements and thereby estimate the full state space of the model. From a practical point of view, this is much more realistic than assuming full state knowledge. An observer is based on a dynamical model and can be used in combination with, e.g., a model-predictive controller. However, relatively little research has been done regarding this topic, and its true potential is still a question.
- More field experiments should be conducted to further investigate if wind farm control can improve the performance of a real wind farm and to obtain data to validate existing models.
- For long-term research challenges in wind energy, see (van Kuik and Peinke, 2016).

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