Robust lidar-based closed-loop wake redirection for wind farm control

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Abstract: Wind turbine wake redirection is a promising concept for wind farm control to increase the total power output of a wind farm. Further, the concept aims to avoid partial wake overlap on a downwind wind turbine and hence aims to decrease structural loads. Controller for wake redirection need to account for model uncertainties due to the complexity of wake dynamics. Therefore, this work focuses first on modeling a wind farm using an uncertain plant description and second on the design of a robust $H_{\infty}$ controller for closed-loop wake redirection by applying standard robust modeling and control techniques on a wind farm. The wake center position is estimated and fed back to a controller which uses the yaw actuator to redirect the wake. For several inflow conditions, step simulations are conducted and system identifications are performed to obtain multiple plant models. This set of models is used to derive a nominal plant and an uncertainty set. Both the nominal model and the uncertainty set define the uncertain plant model. The robust controller is then designed showing promising results in a medium-fidelity CFD simulation model with time-varying inflow conditions.

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Keywords: Control of renewable energy, wind energy, wind farm control, wake redirection, robust control, lidar-based control

1. INTRODUCTION

Wind energy is a key technology to meet future renewable energy goals. In past decades, wind energy has developed from a niche to a reliable technology for power production although it has a lower energy per area factor compared to conventional power plants. Pushing this factor to a higher level makes wind energy production more efficient and competitive. In the past, this was mainly done by increasing the wind turbine size. In recent years, clustering wind turbines to a wind farm also increases the efficiency of wind energy power since grid infrastructure is shared. However, by clustering wind turbines, flow interactions between wind turbines play a relevant role. Due to them, a wind turbine in a wake of an other wind turbine produces less power and suffers higher loads due to wake deficit and increased turbulence intensity in the wake. The idea of wind farm control is to take the wake interactions into account while evaluating controllers. Since wake behavior is complex, model errors will most likely occur. This motivates studying the inclusion of uncertainty in the model and evaluate robust controllers for such an uncertain plant.

To increase the total power output of a wind farm, two main wake control concepts have been considered in the last years: axial-induction-based control, and wake redirection control, (see Annoni et al. (2016) and Fleming et al. (2014), respectively). The work in this paper contributes to the field of wake redirection control. See Boersma et al. (2017) for a summary of current wind farm control activities.

Wake redirection has shown promising results in increasing the total power output of an high-fidelity wind farm model, see Gebraad et al. (2016); Fleming et al. (2014). Further, in Raach et al. (2016a), closed-loop wake redirection control increased the power output of an engineering wind farm model even higher. The general idea of wake redirection is to deflect the wake by either yawing the wind turbine or by cyclic blade pitching (see Fleming et al. (2015, 2014)) such that the performance of downwind turbines increases. Having the ability to deflect the wake gives an additional degree of freedom when controlling a wind farm. Partial wake overlaps can be avoided and the total power output can be increased. This motivates the investigation of more reliable solutions for the wake redirection concept and to also include remote sensing devices like lidar.

Lidar-based closed-loop wake redirection was first presented in Raach et al. (2016b,a). In the following, this concept is reviewed and applied on a uncertain plant with which a robust controller is evaluated. The importance of including uncertainty in the model stems from the fact that wake dynamics are complex (nonlinear and time-varying). Hence modeling using
Wake redirection has shown promising results in increasing the current wind farm control activities. Current wind farm control concepts have been considered in the last years: to increase the total power output of a wind farm, two main aspects have been studied. In the past, this was mainly done by increasing the wind turbine rotor diameter, which increases the energy per area factor. Although it has a lower energy per area factor compared to larger turbines, it also increases the efficiency of wind energy power since grid connection size. In recent years, clustering wind turbines to a wind farm is being considered, while evaluating controllers. Since wake behavior is complex, due to them, a wind turbine in a wake of an other wind turbine produces less power and suffers higher loads due to wake deficit. The general idea of wake redirection is to deflect the wake to increase the performance of downwind turbines. Having the ability to deflect the wake gives an additional degree of freedom when to also include remote sensing devices like lidar. This concept and to also include remote sensing devices like lidar.

The term $f_k$ represents the turbines while $u = [u^T \ v^T]$ and $p$ represent the flow velocities and pressure, respectively. The air density $\rho$ and the viscosity $\mu$ are considered to be constant. The governing equations are resolved numerically using a spatial and temporal discretization scheme. The discrete state variables $u_k, v_k$ and $p_k$ at time step $k$ are arranged according the grid points, e.g.,

$$u_k = [u_k, u_{k+1}, \ldots, u_{N_x}, v_k, v_{k+1}, \ldots, v_{N_y}, p_k, p_{k+1}, \ldots, p_{N_z}]^T.$$  \hfill (3)

The constants $N_x$ and $N_y$ are the number of grid points in the $x$- and $y$-direction respectively. Re-writing the obtained set of equations results in the following set of nonlinear algebraic difference equations:

$$\begin{pmatrix} A_1(u_k, v_k) & 0 & B_1 \\ 0 & A_2(u_k, v_k) & B_2 \\ b_1 & b_2 & b_3 \end{pmatrix} \begin{pmatrix} u_{k+1} \\ v_{k+1} \\ p_{k+1} \end{pmatrix} = \begin{pmatrix} b_1(u_k, v_k) + f_1(u_k, v_k) \\ b_2(u_k, v_k) + f_2(u_k, v_k) \\ b_3 \end{pmatrix},$$  \hfill (4)

with $n = n_x + n_y + n_z$ and $u_k \in \mathbb{R}^{n_x}, v_k \in \mathbb{R}^{n_y}, p_k \in \mathbb{R}^{n_z}$ the velocity vectors in the $x$-direction, $y$-direction and the pressure vector at time $k$, respectively. Each component of $u_k, v_k$ and $p_k$ represents at time $k$ a velocity and pressure respectively at a point in the field defined by the subscript. Computational cost for solving this set of equations is kept low by exploiting sparsity and structure. The terms $b_1(u_k, v_k)$, $b_2(u_k, v_k)$ and $b_3$ represent the boundary conditions and the terms $f_1(u_k, v_k)$ and $f_2(u_k, v_k)$ the turbines. Both will be described next.

Boundary and initial conditions For the $u_k$ and $v_k$ velocity, first order conditions are prescribed on one side of the grid related to the ambient inflow defined by $u_0$ and $v_0$. Zero stress boundary conditions are imposed on the other boundaries. For the initial conditions, all $u_k$ and $v_k$ velocity components in the field are defined as $u_0$ and $v_0$, respectively, the boundary velocity components. The initial pressure field is set to zero.

Turbine model According to momentum theory, the following forcing term can be defined:

$$f_k = C_T(a_k) \frac{1}{2} \rho (U^\infty_k)^2 \Delta x,$$  \hfill (5)

with thrust coefficient $C_T(a_k)$ depending on the axial induction factor $a_k$, rotor upwind velocity $U^\infty_k$ and $\Delta x$ the spatial discretization of the rotor disk. The following expression for $C_T(a_k)$ is proposed in Marshall (2005) and used in WFSim:

$$C_T(a_k) = \begin{cases} \frac{4a_kF(1-a_k)}{8} & \text{if } 0 \leq a_k \leq 0.4 \\ \frac{36F-40}{9}a_k + \frac{50-36F}{9}a_k^2 & \text{if } 0.4 < a_k < 1 \end{cases}$$  \hfill (6)

The scaling factor $F$ is set to 1.75. Since $U^\infty_k$ is difficult to measure in a wind farm, it is more realistic to write the force in terms of the rotor velocity. The following relations are defined:

$$\beta = \frac{a_k}{1-a_k}, \quad U^\infty_k = \frac{U_k^\infty \cos(\phi_k - \phi)}{1-a_k}, \quad U_k^\infty = \sqrt{(u_k^2 + (v_k^2)^2),}$$  \hfill (7)

with $U_k^\infty$ the flow velocity vector at the rotor with direction defined by the wind direction angle $\phi_k$ and the yaw angle $\gamma_k$ of the turbine (see Fig. 2). Substituting these relations in Eq. (5) yields the force expression $S_k$:

$$f_k = \frac{1}{2} \rho C_T(\beta_k) [U_k^\infty \cos(\phi_k - \phi_k) + \beta_k]^2 \Delta x.$$  \hfill (8)

The forces in the $x$- and $y$-direction are now defined as:

$$f_k^x(u_k, v_k) = -f_k \cos(\gamma_k), \quad f_k^y(u_k, v_k) = f_k \sin(\gamma_k).$$  \hfill (9)
In this work, a relatively simple wake center estimation approach is used due to the homogeneous atmospheric conditions. To estimate the wake position, the wind speed profile at a defined measurement distance behind the wind turbine is used (here 2.5 times the rotor diameter). There, the area center point between the two points where the wind speed is first below 93% of the free stream velocity $u_{ref}$ from each side is computed. The center point is then used as an estimation of the wake position. In the future, when using lidar measurement data to estimate the wake position, more advanced methods like a model-based wake tracking approach is needed (see e.g. Raach et al. (2016b)).

3. UNCERTAIN MODEL FOR CONTROLLER DESIGN

In the following, multiple identification procedures are performed on the nonlinear medium-fidelity CFD model described in Sec. 2.1 for different atmospheric conditions. The objective is to obtain an uncertain linear model of the form:

$$G_p(s) = G_0(s) \left(1 + W(s) \Delta(s)\right) \quad \text{with} \quad \Delta(s) \in \Delta$$  \hfill (9)

that is required for the robust $\mathcal{H}_\infty$ controller synthesis used in this paper. The input of (9) is the yaw angle and the output is the wake centerline. The procedure is the following: 1) identify several models, 2) calculate a nominal model representative of the identified models, and 3) define the uncertainty set.

3.1 Model identification setup

Step responses are used to estimate system dynamics and obtain a model for each step simulation because they excite specifically those dynamics we want to control. In this work, we conduct simulations for three different wind speeds, 6 m/s, 8 m/s, and 10 m/s, and within each wind speed simulation, five $\Delta 5$ deg steps starting from 0 deg to 25 deg are applied by the yaw actuator. The measurements are used in the model identification procedure to estimate the dynamics. To obtain offset free models only the transient behavior in the output is used for model identification.

Altogether, fifteen steps are analyzed and fifteen models are identified. The step simulation results can be seen in Fig. 3. The two main aspects in which they differ are the steady-state amplitude and the dynamical behavior. These differences are due to the changing inflow conditions which change the propagation of the flow. Further, all models show inverse response behavior (non-minimum phase behavior) that limits the achievable closed-loop bandwidth.

3.2 Model identification

There are several methods to obtain a model from input-output time simulations. Here, a method of the Model Identification Toolbox of Matlab is used to estimate a continuous transfer function with a predefined number of poles, zeros, and a time delay. For more information on the methodology of the model identification see Ljung (1999). The recorded input (yaw angle) and the recorded output (estimated wake center), are used in the model identification.

As mentioned, the number of poles and zeros have to be predefined. For this work, the number of zeros and poles are chosen in a way that the identification results in a normalized root mean squared error of less than 5% between the model and the recorded output. $n_z = 2$ zero, and $n_p = 5$ poles are set for each identification. This yields a set of models of the form:

$$G_i(s) = \frac{K_i(z_{11}s+1)(z_{12}s+1)}{(p_{11}s+1)(p_{12}s+1)(p_{13}s+1)(p_{14}s+1)(p_{15}s+1)}$$  \hfill (10)
with $p_{lm}$ the poles, $z_{lm}$ the zeros, and $K_l$ the static gain of the identified models $G_l(s)$ for $l = \{1, 2, \ldots, 15\}$. In Fig. 4 the bode plot of all identified models $G_l(s)$ for wind speeds of 6m/s, 8m/s, and 10m/s is presented.

3.3 Uncertainty

The idea of robust control is to ensure stability and performance for a set of models. This set is defined as:

$$G_p(s) = G_0(s)(1 + W(s)\Delta(s)) \tag{11}$$

with the nominal plant $G_0(s)$, a weighting filter $W(s)$, and uncertainty $\Delta(s)$. In this paper we have a SISO system assuming to have complex uncertainty hence $\Delta \in \mathbb{C}$ with property $\|\Delta(s)\|_{\infty} \leq 1$. In order to define the nominal model $G_0(s)$ we, for each frequency $\omega$, first compute:

$$|g_0(i\omega)| = \frac{1}{m} \sum_{i=1}^{m} |G_i(i\omega)|,$$

$$\angle g_0(i\omega) = \frac{1}{m} \sum_{i=1}^{m} \angle G_i(i\omega), \tag{12}$$

with $\angle g_0(i\omega)$ defined as the average phase of $G_i(s)$ for the frequency $\omega$ and $|g_0(i\omega)|$ the average amplitude. $m$ is the number of considered models ($m = 15$). The average model for the frequency $\omega$ is then defined as:

$$g_0(i\omega) = |g_0(i\omega)|\angle g_0(i\omega), \tag{13}$$

and the bode plot of it is shown in Fig. 4 compared to the identified models $G_l$. In order to obtain an equivalent model structure as defined in (10), an identification is performed on $g_0(i\omega)$ resulting in the nominal plant $G_0(s)$. Having obtained the nominal plant $G_0(i\omega)$ the uncertainty set can be calculated by evaluating

$$L_l(i\omega) = \left| \frac{G_l(i\omega) - G_0(i\omega)}{G_0(i\omega)} \right|, \tag{14}$$

for all $l$ models. The amplitude of the set is plotted in Fig. 5. The weighting filter $W(s)$ determines the uncertainty size and should have the property

$$W(i\omega) \geq L_l(i\omega). \tag{15}$$

In order to ensure this property, the following expression can be used to define the amplitude of $W(s)$ for the frequency $\omega$:

$$|W(i\omega)| = \max_l \left| \frac{G_l(i\omega) - G_0(i\omega)}{G_0(i\omega)} \right|, \tag{16}$$

Since we assume $W(s)$ to be without right-half-plane zeros, the uncertainty weight is uniquely defined by its amplitude response given in (16). It is interesting to have a low order weighting filter because this order will, i.a., determine the controller order. Hence the choice of this order is important, we fit a fixed order transfer function on $W(s)$ (6th order). In the following section, a controller will be designed for the uncertain plant.

4. CONTROLLER DESIGN

In the previous section, the uncertain plant $G_p$ has been defined. Note that for the sake of simplicity, we omit, in the remainder of this paper the frequency dependency of the transfer functions. In the remainder of this section, the controller design using the uncertain plant will be presented.
5. RESULTS

In this section, the robust controller design results are analyzed and compared to a nominal $H_\infty$ controller. Then, the controller performances are analyzed for all fifteen models. Finally, the robust controller is used in the CFD model WFSim to control the wake position under varying atmospheric inflow conditions.

5.1 Controller evaluation

A nominal $H_\infty$ controller is designed like presented in Raach et al. (2016a) using the performance weights as defined in (19). The controller design achieves a controller resulting in $\|N\|_\infty = 0.99$. First, in Fig. 7 the Bode plot of the robust and the nominal $H_\infty$ controller are shown. Clearly, the differences between the two controllers can best be seen in the high frequency region.

As a next step, the performance of both controllers is evaluated for the nominal plant. Fig. 8 shows the sensitivity $S$ the controller sensitivity $KS$ and the complimentary sensitivity $T$ obtained with the nominal and the robust controller. Clearly, differences in the controller sensitivity between $10^{-2}$ and $10^{0}$ Hz are observable.

Finally, the sensitivity and the controller sensitivity are analyzed for all fifteen plants $G_i(s)$. Fig. 9 presents the results of the performance analysis of the robust $H_\infty$ controller. As expected, the controller meets the desired performances for all plants $G_i(s)$.

5.2 Simulation results

The robust $H_\infty$ controller is applied in the WFSim simulation model to control the wake position. To evaluate the ability to control the wake position under various atmospheric conditions, the inflow is continuously increased from 6 m/s to 10 m/s and exemplary set point changes are applied. See Fig. 10 for flow snapshots at different times during the simulation. Further, time series results of the estimated wake center and the input signal are given. Altogether, the controller performs well for the varying wind speeds and the desired set point changes. Only small differences in the wake position can be observed in accordance to the performance evaluation in Fig. 9.
As a next step, the approach will be combined with lidar wake tracking methods and transferred to a high-fidelity CFD model to show its applicability in complex flow situations. A controllability and observability analysis should be performed in future work. Further, the controller will be extended to also consider axial induction control.

REFERENCES


