Wind Turbine Wake Estimation and Control Using FLORIDyn, a Control-Oriented Dynamic Wind Plant Model

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Abstract—In this paper we present estimation and control results for wind plants, based on FLORIDyn, a novel control-oriented dynamic model for wake interaction effects between wind turbines in a wind plant. The model predicts wake locations, effective flow velocities, and electrical energy production at each turbine as a function of the control degrees of freedom of the turbines. The model includes the dynamic wake propagation effects that cause time delays between control-setting changes and the response of downstream turbines. These delays are a function of the state of the flow field in the wind plant. The model has a state-space structure combined with a nonlinear feedback term. A Kalman filter is developed for the model that corrects the flow field predictions using wind turbine power production measurements. The computational complexity of the model is small enough that it has the potential to be used for optimizing the control reference signals for improved wind plant control, as demonstrated in a case study.

I. INTRODUCTION

Because a wind turbine extracts energy from the airflow, it has a wake downstream of its rotor in which the wind velocity is reduced with respect to the freestream velocity. Downstream from the rotor the wake expands, and turbulent mixing and diffusion cause the wake velocity to gradually recover towards the freestream velocity. In a cluster of wind turbines (a wind plant), the wake of one turbine can overlap with another turbine rotor, which affects the electrical power production and loads on that second turbine. The topology and amount of wake interaction depend on time-varying atmospheric conditions (e.g., inflow speed, direction, and turbulence) and on the control settings of each turbine. The rotor speed and pitch angles of the blades affect the rotor axial induction and thus the wake velocity deficit [1]. The rotor yaw angle affects both the velocity deficit and direction of the wake [2], [3].

In [4], the FLOW Redirection and Induction in Steady-state (FLORIS) model was developed—a simplified control-oriented model that predicts the steady-state characteristics of wakes in a wind plant in terms of its deflection and velocity profile as a function of the axial inductions and yaw angles of the wind turbine rotors. Although this static model can be used for optimizing control settings, it does not take into account the fact that the flow field further downstream of a turbine responds with a significant delay to a change in turbine control settings because the flow takes some time to move downstream. In [5] we extended the FLORIS model to the FLOW Redirection and Induction Dynamics (FLORIDyn) model that takes into account these delays in the wake effects. The delays are dependent on the dynamics of the velocity profile in the wake, which in turn are dependent on the turbine control. An important feature of the FLORIDyn model is that only two new tunable parameters were introduced in this dynamic extension. The model consists of a linear state-space structure that describes the wake propagation and a nonlinear feedback term that describes the properties of the wake (recovery, deflection, and expansion).

In this paper, we exploit the structure of the FLORIDyn model to develop a Kalman filter that makes corrections on the predicted flow field on the basis of data measured at the turbine (power production and control settings). Further, we demonstrate in a simulation case study that the model has the potential to be used for optimizing the control reference signals for improved wind plant control.

The outline of this paper is as follows. In Section II we briefly describe the FLORIDyn model. In Section III the flow-correction Kalman filter is developed. Section IV provides a control case study. Finally, we present our conclusions in Section V.

II. THE FLORIDYN DYNAMIC WAKE MODEL

In this section, we provide a short overview of the FLORIDyn wake model. A more detailed description is presented in [5].

In the model, a distinction is made between turbines in the wind plant that, relative to the wind direction, are positioned in the front (and therefore are not overlapped by the wakes) and other turbines further downstream. Index \( t \in \mathcal{P} \) is used to count the wind turbines, where \( \mathcal{P} \) represents the set of all turbines in the plant. Front turbines are included in the subset \( \mathcal{F} \subset \mathcal{P} \), and downstream turbines in the subset \( \mathcal{D} = \mathcal{P} \setminus \mathcal{F} \). The power productions of the downstream turbines are estimated as:

\[
P_T(t,k) = \frac{1}{2} \rho \left( \frac{A_T}{C_p} \right) u_T(t,k)^3 \forall t \in \mathcal{D}
\]

where index \( k \) denotes the discrete time steps, \( u_T \) is the effective wind speed at the turbine, \( A_T \) is the rotor swept
downstream and in the outer wake zones, because flow velocity is higher there and the positions of the TrPs are adjusted such that a mass of air can be assumed to flow from one TrP to the next in a time step $\Delta t$.

The wake reduction factors $r_T$ at a downstream turbine $t \in \mathcal{D}$ are dependent on the control settings of the upstream turbines. Because the effects have to propagate through the wind field, there are time delays between control changes at upstream turbines and their effect on the induced wind speed reduction $r_T$ at the downstream turbines. Also, there are time delays between the freestream speeds $U_T$ measured at the front turbines and the freestream speeds $U_T$ active at the downstream turbine. The time delays are dependent on the velocity profile in the wake. Therefore, the FLORIDyn model makes an estimate of the full wake velocity profile and includes a simplified model for the wake propagation, illustrated in Fig. 1. Because the outer parts of the wake recover to the freestream speed faster, the cross-wind profile of a wake of a turbine $t$ is divided into 7 wake zones, counted with index $z$, each with different recovery properties (see Fig. 2). In each wake zone, we define an $N_p$ number of points (Tracking points or TrPs), counted with index $p$, for which the velocities will be calculated. Using these tracking points, a simplified model of the wake propagation is implemented, illustrated in Fig. 1. This wake propagation model takes on the state-space form introduced in the following equations. In each time step of simulation, the model adjusts the downwind positions of the TRPs, $x_{t,z,p}$, based on the FLORIS-predicted velocity profile in such a way that a mass of air will move from one TRP to the next in one time step using the following
state-space description:

\[
\begin{bmatrix}
\dot{x}_{t,z,1}(k+1) \\
\dot{x}_{t,z,2}(k+1) \\
\vdots \\
\dot{x}_{t,z,N_p}(k+1)
\end{bmatrix}
= A
\begin{bmatrix}
x_{t,z,1}(k) \\
x_{t,z,2}(k) \\
\vdots \\
x_{t,z,N_p}(k)
\end{bmatrix}
+ B \begin{bmatrix}
0 \\
1 \\
\vdots \\
0
\end{bmatrix}
\begin{bmatrix}
x_T(t) + \Delta T A z
\end{bmatrix}
\forall t \in \mathcal{P}, z \in \{1, \ldots, 7\}
\]

(4)

where \( u_{t,z,p} \) are the estimated velocities at the TrPs and \( \Delta T \) is the sample time. Then we assume that with a mass of air moving from one tracking point in each time step, the freestream wind speed measured at an upstream turbine is passed on from one tracking point to the next one downstream. A state-space model that describes this has the form:

\[
\begin{bmatrix}
U_{t,z,1}(k+1) \\
U_{t,z,2}(k+1) \\
\vdots \\
U_{t,z,N_p}(k+1)
\end{bmatrix}
= A
\begin{bmatrix}
U_{t,z,1}(k) \\
U_{t,z,2}(k) \\
\vdots \\
U_{t,z,N_p}(k)
\end{bmatrix}
+ BU_T(t,k)
\]

(5)

Similarly, we 'pass on' the yaw angles \( \gamma_t \) and axial induction factors \( \alpha_T \) measured at the upstream turbines to find their locally effective values at each TrP \( (y_{t,z,p}, a_{t,z,p}) \), using a state-space description of the above form. At each time step \( k \), the effective reduction factor of each wake zone \( \tilde{z} \) of an upstream turbine \( \tilde{t} \), at a tracking point \( p \), denoted as \( r_{\tilde{t},\tilde{z} \to t,z,p} \), is calculated as a nonlinear function of those locally effective control settings \( y_{\tilde{t},z,p}, a_{\tilde{t},z,p} \) and of the downstream distance (as the wake moves downstream, its velocity will recover to the surrounding wind velocity; therefore the reduction factor approaches zero). The function definition is provided in [5]. Next, the wind speed at each tracking point is estimated by applying those reduction factors on the locally effective freestream wind speed, \( U_{t,z,p} \), as follows:

\[
u_{t,z,p} = U_{t,z,p} \prod_{(\tilde{t},\tilde{z}) \in \mathcal{E}_{t,z,p}} \left(1 - r_{\tilde{t},\tilde{z} \to t,z,p}\right)
\]

(6)

where \( \mathcal{E}_{t,z,p} \) is the set of wake zones \( \tilde{z} \) of turbines \( \tilde{t} \) that are overlapping with the TrP \( p \). Also, crosswind displacements of the TrPs (resulting from yaw-induced wake deflection) and the local wake expansion are calculated from the locally effective \( y_{t,z,p}, a_{t,z,p} \) through a nonlinear function based on the FLORIS model.

At the downstream turbines \( t \in \mathcal{D} \), the reduction factors induced by the wake zone \( \tilde{z} \) of an upstream turbine \( \tilde{t} \), denoted as \( r_{\tilde{t},\tilde{z} \to t} \), are calculated by interpolating the effective reduction factors at nearby TrPs. To combine the effect of the different wake zones, we use a weighting method based on the overlap area of each zone \( \tilde{z} \) of the upstream turbine \( \tilde{t} \), with the rotor of turbine \( t \), denoted as \( A_{\tilde{t},\tilde{t},\tilde{z} \to t,z} \) (see Fig. 2). Then the total effective speed reduction factor at the turbine \( t \), \( r_T(t,k) \) is estimated as follows:

\[
r_T(t,k) = \sum_{i \in \mathcal{P}, t,z \in \mathcal{T}(t)} \left( \sum_{k=1}^{7} A_{\tilde{t},\tilde{t},\tilde{z} \to t,z} \right)^2
\]

(7)

and similarly, the effective wind speed at a turbine is estimated from interpolating the freestream speeds effective at the TrPs and weighting by the overlap areas of the wake zones:

\[
U_T(t,k) = \sum_{i \in \mathcal{P}, t,z \in \mathcal{T}(t)} \sum_{k=1}^{7} A_{\tilde{t},\tilde{t},\tilde{z} \to t,z} U_{\tilde{t},\tilde{t},\tilde{z} \to t,z}(k)
\]

(8)

Using the effective velocity reduction factors \( r_T \) and freestream wind speeds \( U_T \) at the downstream turbines, the effective wind speeds at the downstream turbines and, finally, their power productions are estimated using (2) and (7).

III. USING A KALMAN FILTER TO CORRECT THE PREDICTED VELOCITY FIELD

The FLORIDyn model describes the velocity profile in the wakes of turbines. Although the time-averaged effect of turbulence on the wake recovery is included through a parametric model of the wake velocity profile, the local fluctuations as a result of turbulence are not included; including a detailed turbulence model would overcomplicate the control-oriented wind plant model. In control engineering, Kalman filters are widely used to reconstruct the state of models from measured data, under the influence of random noise influences, and model inaccuracies [6]. In this section, we present a method to correct the errors between FLORIDyn and higher-fidelity models that can at least partly be attributed to turbulence. The method uses Kalman filtering techniques to reconstruct the state of the FLORIDyn model from measurements at the turbine (electrical power production and control settings). Because these are measurements available on a wind turbine, it is expected that the techniques can be extended for application on real wind plants. Furthermore, it is shown that if we focus on correcting the model-predicted velocity field by adjusting the freestream velocities at different TrPs, the Kalman filter takes on a relatively simple form.

The implementation of the Kalman filter is explained in Section III-A. A simulation case study of applying the filter is presented in Section III-B.

A. Description of the Kalman filter

Eq. (8) defines a time-varying mapping between the freestream speeds effective at some of the TrPs and the effective freestream speed at the turbines. We can write this mapping as:

\[
\tilde{U}_{T,\tilde{t}}(k) = C_U(k) \tilde{U}(k)
\]

(9)

with \( C_U(k) \) a sparse, time-varying matrix, \( \tilde{U}_{T,\tilde{t}}(k) \) a vector in which all the turbine-effective freestream speeds at the downstream turbines at time step \( k \),
\{U_{T}(t,k) \forall t \in \mathcal{D}\}$, are stacked, and $\hat{U}(k)$ a vector in which the freestream velocities at each TrP in the wind plant, $\{U_{t,z,p}(k) \forall t,z \in \{1, \ldots, T\}, p \in \{1, \ldots, N_{p}\}\}$, are stacked. Also, we combine the update equations \((5)\) for all wake zones of all downstream turbines $t \in \mathcal{D}$ in a system in the state-space form:

$$\hat{U}(k+1) = A(k)\hat{U}(k) + B_{\mathcal{D}}\hat{U}_{\mathcal{T},\mathcal{D}}(k) + B_{\mathcal{X}}\hat{U}_{\mathcal{T},\mathcal{X}}(k) + w(k)$$

where $A$, $B_{\mathcal{D}}$, and $B_{\mathcal{X}}$ are matrices in which the matrices $A$ and $B$ are stacked in block-diagonal form. In the above state-space form, we make a distinction between the input vector consisting of the freestream velocities effective at the downstream turbines, $\hat{U}_{\mathcal{T},\mathcal{D}}$, and the input vector consisting of the freestream velocities effective at the front turbines, $\hat{U}_{\mathcal{T},\mathcal{X}}$. The vector $w$ is a noise process describing the effect of turbulence and model inaccuracy. Equations \((9)\) and \((10)\) can be combined in the following form:

$$\hat{U}(k+1) = \tilde{A}(k)\hat{U}(k) + B_{\mathcal{X}}\hat{U}_{\mathcal{T},\mathcal{X}}(k) + \tilde{w}(k)$$

where $\tilde{A}(k) = A + B_{\mathcal{X}}C_{U}(k)$ and the velocity effective at the turbines are calculated using \((6)\) and then the velocity effective at the turbines is calculated using \((3)\). Note that the combination of \((2)\) and \((9)\) can be written as:

$$\hat{w}_{\mathcal{T},\mathcal{X}}(k) = C_{a}(k)\hat{U}(k) + \hat{v}(k)$$

where $C_{a}(k)$ is a sparse, time-varying matrix, $\hat{w}_{\mathcal{T},\mathcal{X}}(k)$ is a vector in which all the turbine-effective wind speeds at the downstream turbines at time step $k$, $\{U_{T}(t,k) \forall t \in \mathcal{D}\}$, are stacked and where $v(k)$ represents output noise. From measurements at the downstream turbines (power, yaw, and axial induction) we can estimate these effective velocities by inverting relation \((11)\), and then we can construct the vector $\hat{w}_{\mathcal{T},\mathcal{X}}(k)$. Then, with this vector as an input, we use a conventional Kalman filter for one-step-ahead prediction of the state of the system with state equation \((11)\) and output equation \((12)\). We follow the definition of the conventional Kalman filter provided in \([6]\). When augmented with this Kalman filter, the system is:

$$\hat{U}(k+1) = \tilde{A}(k)\hat{U}(k) + B_{\mathcal{X}}\hat{U}_{\mathcal{T},\mathcal{X}}(k) + K(k)\left[\hat{w}_{\mathcal{T},\mathcal{X}}(k) - \hat{w}_{\mathcal{T},\mathcal{X}}(k)\right]$$

where $\hat{U}_{\mathcal{T},\mathcal{X}}$ represents the effective velocities reconstructed from measurements and $\hat{w}_{\mathcal{T},\mathcal{X}}$ the model estimate of those velocities. At each time step the Kalman gain $K(k)$ is updated as:

$$K(k) = \tilde{A}(k)P(k|k-1)C_{a}(k)^{T} \times (R + C_{a}(k)P(k|k-1)C_{a}(k)^{T})^{-1}$$

$$P(k+1|k) = \tilde{A}(k)P(k|k-1)\tilde{A}(k) + Q - K(k)\tilde{A}(k)P(k|k-1)C_{a}(k)^{T}$$

where $Q$ is the covariance matrix of the noise $\hat{w}$, and $R$ is the covariance matrix of the noise $\tilde{v}$ (for simplicity we assume the two noise sources, $\hat{w}$ and $\tilde{v}$, are not correlated). If we assume that noise $\hat{w}$ describes velocity variations at each TrP as a consequence of turbulence, we can interpret the covariance matrix of $\hat{w}$ as a matrix that describes the correlation between the turbulence at the different TrPs. Therefore, if we consider matrix $Q$ as a tuning parameter, it makes sense to simplify the tuning problem by parameterizing $Q$ as follows:

$$Q = \begin{bmatrix} 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 0 \end{bmatrix}$$

with $\hat{Q} = \begin{bmatrix} q_{0} & q_{1} & \cdots & q_{N_{p}} \\ q_{1} & q_{0} & \cdots & \vdots \\ \vdots & \ddots & \ddots & q_{1} \\ q_{N_{p}} & \cdots & q_{1} & q_{0} \end{bmatrix}$

Now, according to the above reasoning, scalar $q_{0}$ can be interpreted as the covariance of the turbulence at each TrP, $q_{1}$ the cross-covariance of the turbulence of one TrP with its neighboring TrP, scalar $q_{2}$ the covariance of the turbulence of two TrPs separated by one other TrP, and so on. We assume that we deal primarily with homogeneous turbulence, for which the correlations are dependent on the relative distance between the points rather than on the specific location \([7]\). In that case, the matrix $Q$ having the structure as in \((16)\), prescribes how well the turbulence remains correlated over distance.

**B. Kalman filtering case study**

In this case study we simulated a small wind plant with a high-fidelity computational fluid dynamics (CFD) wind plant simulator, called Simulator for On/Offshore Wind Farm Applications (SOWFA) \([8]\), and with the FLORIDyn control-oriented model both with and without the Kalman filter active. The Kalman filter uses the SOWFA-predicted turbine power outputs to correct the FLORIDyn-predicted wind field according to the implementation as described in the previous section.

The simulated wind plant consists of 2 rows with 3 turbines each, with a spacing of 5 rotor diameters in the row direction and 3 rotor diameters in the column direction. After 400 s, the yaw angles of upstream turbines are misaligned with the incoming wind direction to redirect the wakes away from the downstream turbines.

The parameters $Q$ and $R$ used in this case are listed in Table \([III]\); they were tuned to minimize the sum of root-mean-square error (RMSE) for each turbine. The parameters of the FLORIDyn model are listed in \([5]\), in which a similar case study was performed but without the Kalman filter applied. Fig. \([4\alpha]\) shows the flow fields predicted by the two models, for
two time instances. As an illustration of the Kalman filtering process, in Fig. 4(b) the corrections are shown that the filter performs on the freestream velocity at the different TrPs upstream of the turbine. The resulting power responses are provided in Fig. 3. Two effects can be seen in the results of this case study: (1) an overall better fit of the power responses is obtained by using the Kalman filter for correction of the wind field and (2), a feature of the Kalman filter is that it is able to correct the response to an initial guess of the unknown state of a system in the first part of a simulation by using measured data. The FLORIDyn model without the Kalman filter only uses measurements at the front turbines to estimate the freestream velocity. Because wake-traveling dynamics are slow, the transient response to the initial guess of the freestream velocity at the downstream turbines is long; therefore there is a large error in the initial response if the initial guess of the flowfield is not accurate. It can be seen in the responses that the Kalman filter can ensure a quicker mitigation of that error by using the measured data on the downstream turbines to ‘reconstruct’ the velocity field in the downstream part of the wind plant.

IV. USING THE FLORIDYN MODEL FOR YAW CONTROL

In this section, we present a case study of how the FLORIDyn model dynamic control-oriented model of wake effects in a wind plant can be used to optimize the control of the wind plant. By optimizing the scheduling of control signals based on the predictions provided by the FLORIDyn dynamic model rather than on a steady-state model as in previous work [4], we account for delays in the wake effects.

In this case study, we consider a scenario in which three turbines are placed in a line with a spacing of 5 rotor diameters. In a FLORIDyn simulation, after 200 s of simulated
time, we emulate a short shutdown of the second turbine through blade feathering by setting the axial induction of that turbine to zero for 200 s. It should be noted that this is an unrealistic reduction of axial induction, which just serves as a proof of the control concept. We aim to optimize the time sequence of yaw settings of the turbines for increased electrical energy production.

To keep the optimization computationally efficient, we used physical reasoning to parameterize a solution for the optimization problem and reduce the search space. We know that if the second turbine in the row will not extract power anymore, the front turbine can decrease its yaw angle to increase power extraction, because it does not have to steer its wake away from the next downstream turbine 2, but from turbine 3 that is standing further downstream. Furthermore, we can assume that turbine 1 will adjust its yaw sometime before turbine 2 switches off, because the wake effect of the yaw change of turbine 1 will reach the downstream turbines with some delay. We let turbine 1 respond to a reference by yawing with a maximum rate of $1^\circ/\text{s}$, and we restrict to positive yaw angles. If we prescribe that turbine 1 will adapt by making a step change on its yaw reference setting, and stepping back to its original yaw setting later, we can parameterize the solution using three parameters: $\Delta \gamma_1(1)$, the size of the yaw reference step change of turbine 1, $k_1$, the time step at which turbine 1 makes the yaw reference step change, and $k_2$, the time step at which turbine 1 steps its yaw back to the initial settings. Using these concepts, we can prescribe the following constraints on the optimization parameters $\Delta \gamma_1$, $k_1$, $k_2$:

$$-\gamma_1(1,0) < \Delta \gamma_1(1) < 0$$
$$0 < k_1 \Delta T < 200 \text{ s}$$
$$k_1 \Delta T < k_2 \Delta T < 400 \text{ s}$$

(17)

where $\gamma_1(1,0)$ is the initial yaw setting of turbine 1 and $\Delta T$ is the sample time.

The initial yaw settings for each turbine are the optimized yaw setting for steady-state operation, which were found using a steady-state model (the FLORIS model). Then, we used the FLORIDyn dynamic model to perform the optimization of parameters $\Delta \gamma_1(1)$, $k_1$, $k_2$ of the adaptive yaw control sequence, with maximum total electrical energy production in the control horizon as the objective. We performed an extensive grid search wherein each parameter set evaluation we simulate the dynamic system response to a particular yaw reference sequence with the FLORIDyn model. In each of these simulations, we used a time step $\Delta T = 5 \text{ s}$ and a total simulated time of 600 s. The grid search of the solution space prescribed by the inequalities (17), was first performed with an incremental step of 5 on $k_1$ and $k_2$ (i.e., 25 s) and $2^\circ$ on $\Delta \gamma_1(1)$, then the parameter search grid was refined around the optimal solution to an incremental step of 1 on $k_1$ and $k_2$ (5 s) and $1^\circ$ on $\Delta \gamma_1(1)$. A total of 735 FLORIDyn simulations are needed to search the parameter space in this way. On average, it takes 0.51 s to evaluate a FLORIDyn simulation of the case in a MATLAB implementation on a 1.6 GHz PC, yielding a total calculation time of 375 s to perform the parameter search. An extensive search was used here to ensure the global optimum was found, but more efficient optimization strategies should be explored to reduce the computation time of finding the optimized control sequences. Still, the computational cost of FLORIDyn is relatively low when compared to a high-fidelity CFD wake model such as SOWFA [4], which takes on the order of days using parallel computing with a few hundred processors.

In Fig.[5] the resulting optimized yaw sequence and turbine power responses as predicted by the FLORIDyn model are shown (‘adaptive yaw’) and compared to the case in which the yaw settings of each turbine are held constant throughout the simulation (‘constant yaw’). Furthermore, the difference in cumulative electrical energy production between the adaptive yaw control and the constant control is shown. It can be seen that a relatively small amount of energy production increase (0.19% of the total energy production) can be gained by the fact that turbine 1 reduces its yaw angle. Turbine 1 yaws at a time interval that is earlier than the interval of the shutdown of turbine 2, such that the wake-traveling delays are accounted for. Fig. [6] shows the wake velocity profiles predicted by FLORIDyn for the adaptive control case with a short description of the different steps in the adaptive yaw control procedure.

V. CONCLUSIONS

Results from the case studies are promising. The wake propagation effects are described by a linear state-space model. This allowed the development of an observer based on a Kalman filter using conventional techniques. The filter makes corrections on the velocities in the wind field to account for model inaccuracies and smaller-scale turbulence effects based on measured power data from the turbines. The control example showed that the scheduling of the yaw settings can be optimized by taking into account dynamic effects in the wakes—mainly consisting of delays that are dependent on the wake velocity profile. However, we did not demonstrate a large increase of wind plant performance by going from control optimization based on a steady-state model, such as the FLORIS model, to a dynamic model, such as the FLORIDyn model. Based on this experience, we expect the main benefit of using a control-oriented dynamic wake model to be that the parameters of such a model can be optimized based on the dynamic response of the wind plant, whereas a static model, such as the FLORIS model, has to be tuned based on data time-averaged over a period in which the wakes are fully propagated through the wind plant. This could be an important benefit when applying model-based control optimization on a real wind plant with continuously changing atmospheric conditions. The atmospheric conditions have an effect on recovery properties of the wakes and thus the model parameters should be adapted. For this purpose, in future work the Kalman filter should be extended to an observer that updates the parameters of the FLORIDyn model without over-fitting to the effects of small-scale turbulence.
Fig. 5: Result of the control case study in Section IV turbine yaw angles (top) and predicted power productions (middle) for the case in which an optimized adaptive yaw control sequence is used and a case in which yaw is held constant. The cumulative difference in energy production that is gained by using adaptive instead of constant yaw control for the simulated scenario is shown in the lower plot.

REFERENCES


