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Identification of turbine clusters during time varying wind direction

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***Abstract*— An efficient strategy for maximizing the power production of a power plant is to control in a coordinated way only turbines that are aerodynamically coupled through wake effects. The implementation of such control strategy requires the knowledge of which clusters of turbines are coupled through wake interaction. In a previous study, we identified turbine clusters in real-time by evaluating the correlation among the power production signals of the turbines in the farm. In this study we reproduce the more challenging scenario with large-scale variation of the wind direction. Different time windows of data needed to compute the correlation coefficients are tested and characterized in term of accuracy and promptness of the identification.**

I. INTRODUCTION

The power production of a turbine in the wake of another can be reduced by 40% - 60% [1], [2], [3]. As a consequence the Annual Energy Production of large wind power plants can be negatively affected by wake interaction depending on the wind variability at the site, turbulence, and layout of the farm [4].

Different control algorithms have been proposed to reduce wake interaction and increase the cumulative power production of wind farms. The common aspect to these control algorithms is the need to consider wind farm collectively rather than optimize each individual turbines separately. When looking at the wind farm in a collective way, turbines wakes play a fundamental role since they may link several turbines in the wind farm through wake interaction. The momentum extracted from the wind by upstream turbines results in the formation of downstream wakes that may impinge on trailing turbines. In this case, the wind farm can be then divided in clusters of turbines coupled through their wakes. Turbines belonging to a cluster are significantly affected by a change in the operating condition of another turbine in the same cluster. On the other hand, a perturbation to a turbine belonging to a cluster, to a good approximation, does not influence turbines belonging to a separate cluster. Breaking down a wind farm into several clusters has the advantage of reducing the complexity of the optimization process [5]. For example, dividing a wind farm of N turbines into M smaller clusters reduces the wind farm optimization problem (consisting of at least N control parameters) to the optimization of M independent smaller problems with L_i control variables each (where L_i is the number of turbines belonging to the i^{th} cluster). This allows reducing the converging time to optimize the wind farm since the optimization of the M clusters can be carried out simultaneously. In addition, each M^{th} cluster consists of a reduced number of turbines respect to the wind farm and thus a smaller number of control parameters that can be optimized. As an example of the potentiality of reducing the optimization computational cost, turbine clustering has been recently implemented in the yaw misalignment optimization tool of FLORIS[6].

Yaw control, i.e. the intentional application of yaw misalignment to upstream turbines, has been shown to be a promising technique to increase the power production of arrays of aligned turbines[7] and of wind farms [8], [9], [10], [11], [12]. The power production of the yawed turbines decreases but their wakes are steered away from the downstream turbines. As a result, the cumulative power production of the turbine array increases. The application of yaw control, thus, relies on the knowledge of which turbines are in the wake of the upstream turbines, i.e. identify the cluster of turbines coupled by the wake interaction. However, in a real wind farm, because of the variability of the wind direction, turbine clusters continuously change.

In our previous work[13], [14], we developed a method to identify turbine clusters based on the correlation of the power production signals among all the turbines in the wind farm. When the method does not find any cluster in the farm, it means that the wake interaction is weak and that yaw control is not effective. While in the previous study we considered 4 different but constant wind directions, in this work we reproduce a more realistic condition where the wind direction varies in time over a span of $60°$.

Large scale variation of the wind direction should promptly be identified in order to switch the wind farm controller from the collective yaw control to the individual controller during the transients and then apply new yaw misalignment configuration based on the new wind direction. The performance of the proposed method is then evaluated by considering also the response to large scale variation of the wind direction. On the other hand, when a new stable wind direction is reached, the wind farm controller should allow the new clusters of turbines to form before applying any power optimization control strategy.

To identify clusters of turbines in real-rime, correlation of power signals need to be computed over a sliding window. In the previous study we considered a fixed time window of 30 minutes. This paper aims to study the sensitivity of the cluster identification to the time window considering both the accuracy and the promptness of the response to the variation of the wind direction.

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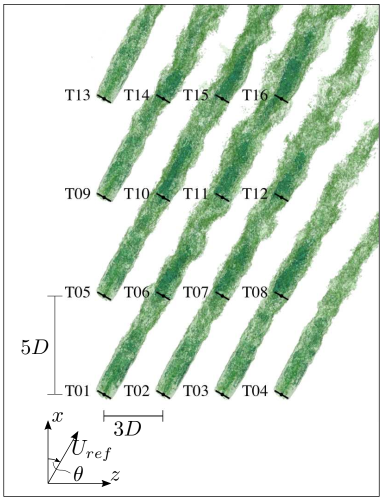

Fig. 1. Layout and turbine labels of the wind farm. The rotor diameter of the turbines is denoted by D and θ is the wind direction (in the instantaneous visualization equal to $30°$).

Section II presents the set up used for the numerical simulation.Section III summarizes the main features of the cluster identification method. Section IV shows the effect of yaw misalignment during wind direction transients. Lastly, sections V and VI respectively show the results of the study and draw the conclusions.

II. Numerical set-up

A virtual wind-farm composed of 16 NREL-5MW reference turbine[15], arranged in 4 rows and 4 columns, is simulated with Large Eddy Simulations (LES). The turbines have a rotor diameter $D = 126$ m, rated wind speed $U_{rated} = 11.4\mathrm{m/s}$ and rated power $P_{rated} = 5\mathrm{MW}$. As shown in figure 1, the turbine spacing in the transversal direction (z direction) is $3D$, while in the longitudinal direction (x direction) the spacing is $5D$. The towers and nacelles are simulated using the immersed boundary method (IBM) implemented by Orlandi & Leonardi[16] and by Santoni et al.[17]. The forces of the rotor acting on the flow are reproduced using the rotating actuator disk model[18]. The disk rotates in time according to the actual blade motion and accounts for both the thrust and tangential forces; the angular speed is determined according to the rotor dynamics and controlled using a standard region II control law, where the generator torque is taken proportional to the square of the generator speed[19]. Additional details about the torque controller can be found in[14]. The nacelle direction is controlled by the individual yaw controller of each turbine. The individual yaw controller operates on the difference between the nacelle direction, α and the wind direction, θ, filtered with a low-pass filter with an RC constant equal to $10s$. The rotation of the nacelle is activated when $|(\alpha - \psi) - \theta| > 2°$, where ψ is the imposed yaw misalignment. If rotation is activated, the nacelle moves with a yaw rate of $0.4°/s$ until reaching the desired orientation.

The average wind speed at the hub height is equal to $U_{hub} = 0.8U_{rated}$. In order to reproduce the atmospheric boundary layer (ABL) at the inlet, turbulence obtained from a precursor simulation is superimposed to a mean velocity profile expressed by the following law:

$$\frac{\overline{U}}{U_{hub}} = \left(\frac{y}{y_{hub}}\right)^{\alpha} \tag{1}$$

where y is the vertical coordinate, y_{hub} is the hub height and α is the shear exponent set to $\alpha = 0.05$. The precursor simulation to reproduce the ABL turbulence was performed as a half-channel with periodic boundary conditions on the sides and free-slip condition on the top. Neutral atmospheric stability conditions were applied. The streamwise component of the wind velocity at height y is denoted by $\overline{U}$ and U_{hub} is the streamwise component of the wind velocity at the hub height upstream of the wind farm. From the superposition of the mean flow of equation (1) and the turbulence from the precursor, the resulting turbulence intensity at the hub height upstream of the wind farm is equal to 11%. The space-averaged wind direction at the inlet upstream of the wind farm varies in time in the interval of $\theta \in [0°, 60°]$ as shown by the black line in figure 2. It should be noted that the local wind direction at any location of the domain may be instantaneously different from the average wind direction due to local turbulence. As an example, the blue line and red lines in figure 2 show respectively the wind direction measured at T01 and T16. Their instantaneous value fluctuates in time depending of the upstream turbulence and the location of the wind turbine in the wind farm. The large-scale wind direction variation adopted for this study and reproduced in figure 2 was inspired by realistic variation in the wind direction from SCADA data of wind farm in North Texas. Using the chosen wind direction variation we want to test the cluster identification algorithm against the most challenging condition where new clusters should be identified in the smallest amount of time possible after a rapid change in the wind direction.

The simulation of the large scale time-varying wind direction is achieved by imposing at the inlet of the simulation domain a variation in time of the two horizontal components of the velocity vector:

$$u(t) = U(t)\cos\theta(t) - W(t)\sin\theta(t) \tag{2a}$$
$$w(t) = U(t)\sin\theta(t) + W(t)\cos\theta(t) \tag{2b}$$

where t is the time and θ is the wind direction; $u(t)$ and $w(t)$ are respectively the components of the velocity in the x and z directions of figure 1. U and W are the instantaneous components of the streamwise and spanwise velocity that are the sum of the mean velocity profile and turbulent fluctuations:

$$U(t) = \overline{U} + u'(t) \tag{3a}$$
$$W(t) = \overline{W} + w'(t) \tag{3b}$$

with $\overline{U}$ is obtained from eq.(1), $\overline{W} = 0$ is the average spanwise velocity, u' and w' are the turbulent fluctuations respectively in the streamwise and spanwise direction obtained from the precursor simulation. Thanks to the periodic

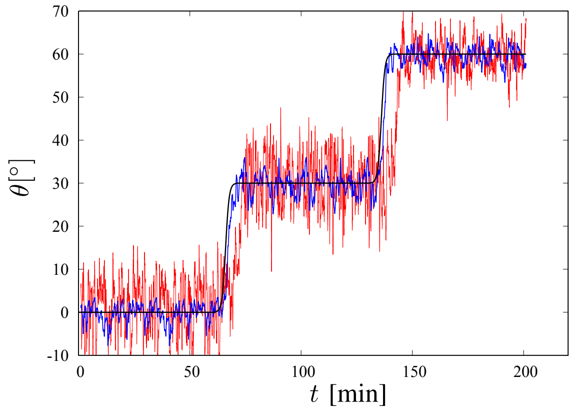

Fig. 2. Time variation of the wind direction: —— space-averaged wind direction upstream of the wind farm; —— the wind direction at T01; —— the wind direction at T16.

boundary conditions at the sides, the turbulent fluctuations from the precursor simulation are prescribed only at the inlet of the simulation domain.

The computational box is designed such that the periodic boundary conditions at the sides does not influence the flow field inside the wind farm. A minimal distance of $5D$ is kept between the inlet/outlet and the respective boundaries of the wind farm. Radiative boundary conditions are applied at the outlet. The vertical size of the domain was kept constant and equal to $10D$ with free slip boundary conditions at the top. The grid resolution in the region of the turbines is $\Delta x = \Delta z = 0.03D$ and $\Delta y = 0.025D$.

III. Cluster identification

Time-lags due to advection must be taken into account when applying any control strategy to large wind farms. Indeed, a change in the wind condition or in the control set point of an upstream turbine affects downstream turbines with a time delay that is proportional to ratio among the turbines and the free stream velocity. For large wind farms this can be of the order of several minutes. As an example, the blue line of Fig.2 shows the wind direction measured by the turbine T01, representative of the upstream turbines, while the red line reports the wind direction measured by the turbine T16, i.e. the most downstream turbine. From the comparison between the blue and red lines, we can observe a time delay of about 5 minutes from the time at which the wind direction starts changing at T01 to the time at which it start changing at T16. Since changes in the wind conditions are convected downstream by the free stream flow, the time delay depends on the average wind velocity upstream of farm. Slower wind velocity implies a lager time delay and vice versa. A rough estimate of the time delay τ^* can be obtained as:

$$\tau^* = d/U_{hub} \tag{4}$$

where d is the extension of the wind farm in the streamwise direction (for example, in the case of $\theta = 30°$ shown in Fig.1, d is equal to the distance between T01 and T16). As noted in [13], the average velocity at which wind disturbances are transported in the wakes corresponds to about $0.8U_f$, where the U_f is the free stream velocity in front of the wind farm. As a consequence, the actual time delay τ is a function also of the wake interaction within the wind farm and can be longer than the estimated τ^*. More stable wakes with less wake recovery will increase the time delay τ since the average wind speed inside the wind farm is reduced. However, the study of this dependence goes beyond the scope of this paper.

In order to identify clusters of turbines in real time we use the correlation of the power production signals of all the turbines in the wind farm as described in [14]. At each time instant, the power production signal of all the turbines is stored for a time window with a-priori determined length. The correlation coefficients are then computed using the data inside the time-window. Turbine pairs coupled by the wake interaction are expected to exhibit a maximum in the correlation for a time delay τ that is function of the distance between the two turbines. Large coherent turbulent structures can correlate the power production of pairs of turbines with random directions. These outliers are filtered out exploiting the coherence in the direction of the pair of turbines that have a high correlation due to wake interaction. In other words, if there is wake interaction within a wind farm, turbine pair with high correlation due to wake interaction will have a coherent direction while turbine pairs correlated by the turbulence will have random directions. Finally, a network of interacting turbines is obtained only for the wind conditions that allow increasing the wind farm power production through collective yaw control. When no clusters are detected, it means that the wake interaction within the wind farm is weak enough that each turbine can be controlled as it was isolated. Such condition happens for example during transients from one direction to another.

In this study we perform a parametric study of the length of the sliding time-window over which the power production correlation has to be computed at each time step in order to identify the turbine clusters with variable wind direction in time. In particular sliding windows of 10, 20, 30 and 40 minutes of power production data are considered for the computation of the correlation coefficients and the identification of the turbine clusters.

IV. Wind direction transients

An implicit hypothesis of yaw control is that an actual energy gain is obtained when the wind direction remains constant for a significant amount of time. Indeed, during the transition from one wind direction to another, the wind direction is not uniform across the wind farm and the imposition of yaw misalignment for wake steering control may actually result in power losses. As an example, Figure 3 shows the cumulative power production of the wind farm when the wind direction changes from from $\theta = 0°$ to $\theta = 30°$. The solid line represents the power production of the wind farm when each turbine is controlled individually. For $\theta = 0°$, 4 clusters of turbines aligned with a wind direction

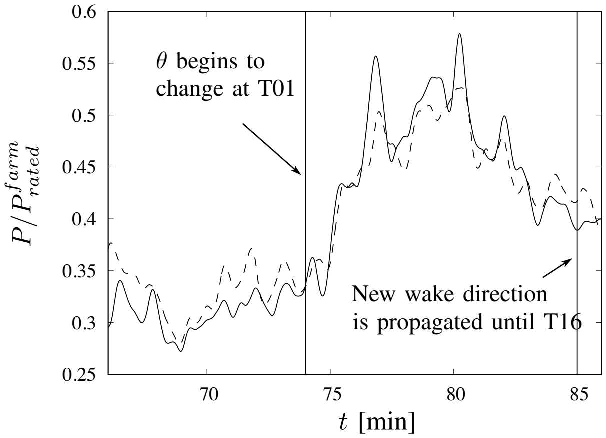

Fig. 3. Time variation of the wind farm cumulative power production during changing wind direction with individual control (——) and with coordinated yaw control (- - - -).

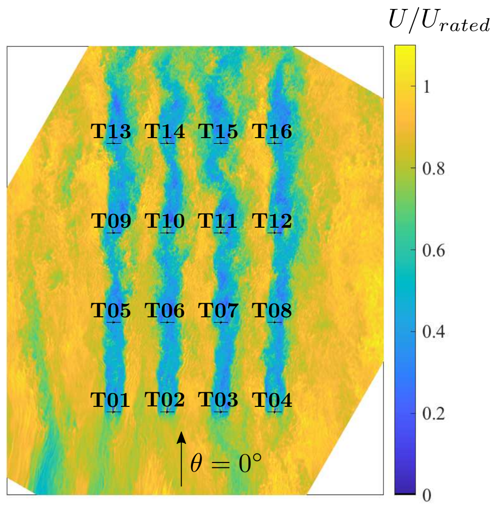

Fig. 4. Instantaneous velocity at the hub height for $\theta = 0°$.

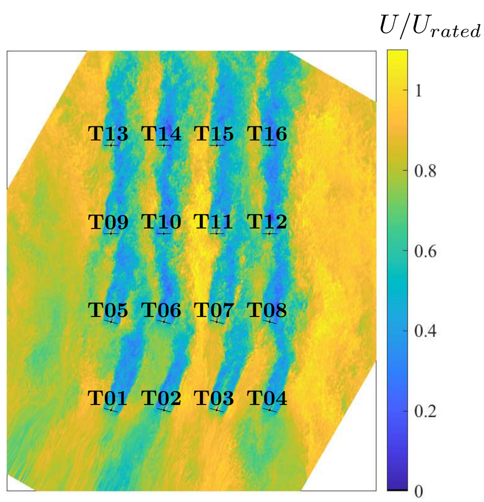

Fig. 5. Instantaneous velocity at the hub height during the transient from $\theta = 0°$ to $\theta = 30°$.

and a turbine spacing of 5D are formed (see Figure 4). Large turbulent structures, obtained from the precursor simulation are visible in front of the and around the wind farm. These turbulent structures are the reason of the fluctuations in the wind direction of T01 shown by the blue line in Figure 2. The wind farm power production is minimum because of the strong wake interaction within the clusters.

When the wind direction starts changing, the farm power production increases until reaching a maximum that corresponds to non-uniform wind direction within the wind farm and very weak wake interaction. Figure 5 shows that during the transient from $\theta = 0°$ to $\theta = 30°$ the direction of the wakes of the most upstream row of turbines (T01, T02, T03 and T04) is significantly different from the wake direction of the turbines in the most downstream row of the turbines in the wind farm (T13, T14, T15 and T16). Since turbine wakes are convected downstream by the local wind, non-uniform wake direction implies non-uniform wind direction within the wind farm.

Finally, when $\theta = 30°$ across all the wind farm, the power production of the wind farm starts decreasing again because of the formation of new clusters of turbines. However, the farm power production for $\theta = 30°$ is higher than for $\theta = 0°$ because of the different cluster configuration with more turbines that face free stream conditions and the larger spacing in the streamwise direction among turbine belonging to the same cluster (see figure 1).

The dashed line in Figure 3 represents instead the wind farm power production when yaw control is applied in order to reduce the wake interaction and maximize the cumulative power production. In particular, using the results in [14], the wind farm is initially optimized for the wind direction $\theta = 0°$ by imposing the following yaw misalignment angles:

- $\psi = -20°$ to the turbines in the two clusters in the West part of the wind farm (T01-T05-T09; T02-T06-T10);
- $\psi = +20°$ to the turbines in the two clusters in the East part of the wind farm (T03-T07-T11; T04-T08-T12);
- no yaw misalignment to the most downstream turbines in each cluster (T13; T14; T15; T16).

This configuration allows to best exploit the blockage effect of the wind farm on the incoming flow to steer the wakes away from the downstream turbines. In this example we impose that the collective yaw controller, does not change the yaw misalignment angles of the turbines until the new wind direction of $\theta = 30°$ is uniform across the wind farm, i.e. when a new set of yaw control angles should be applied. At the beginning, when $\theta = 0°$, the power production of the wind farm controlled with collective yaw controller exceeds the power production of the individually controlled wind farm thanks to the optimized yaw misalignment angles. Then, when the wind direction starts changing at the most upstream turbine of the wind farm (T01), the power production of the individually controlled wind farm outperforms the power production of the wind farm where yaw control is applied. This is due to the fact that during the transition from $\theta = 0°$ to $\theta = 30°$, the wake interaction among turbines in the wind farm is much reduced as shown in Figure 5. In order to avoid power losses during transients of the wind direction, the cluster identification algorithm must be able to promptly identify the change in the wind direction and communicate to the farm controller to switch from the collective to the individual control approach.

V. Results

The performance of the cluster identification algorithm can be evaluated in terms of two main criteria:

- the accuracy of the identification, i.e. the number of correct identification of turbine clusters;
- the promptness of the response, that is the time delay that the algorithm takes to identify a change in the cluster configuration.

A. Accuracy

The accuracy of the identification is computed as:

$$Accuracy = 1 - \frac{N.\ incorrect\ identifications}{N.\ base\ connections} \quad (5)$$

where the *N. incorrect identifications* is the sum of the waked turbine pairs that are not identified (false negative) and turbine pairs that are incorrectly identified as coupled by the wake interaction (false positive). A *base connection* is each turbine pair whose cumulative power production increases after the application of yaw misalignment. In a previous study[13], we determined the turbine pairs coupled by the wake interaction by comparing their cumulative power production before and after the application of yaw misalignment to the upstream turbine. For each wind direction, we use this network of base connections as reference to evaluate the performance of the cluster identification algorithm.

Figure 6 shows how the accuracy of the identification change with the increasing length of the sliding time window used to compute the correlation coefficients. A too small time window does not allow the flow to fully propagate across the wind farm. Therefore, signals of the power production are mostly uncorrelated and clusters cannot be identified. This is also expected from a theoretical point of view. Indeed, due the characteristic time of the wake propagation in the wind farm, any flow disturbance introduced by an upstream turbine affects the most downstream turbines with a time delay that is function of the free stream velocity and wind farm size (see eq. (4)).

With larger time windows to compute the correlation coefficients, the accuracy of the identification increases up to about 80% for a time window of about 30 minutes. This value of the accuracy usually corresponds to the presence of a maximum 2 false negatives in the entire wind farm. For a time window of 40 minutes, the accuracy reaches the value of 90%. However, this increase in the accuracy is payed by a reduction in the promptness of the cluster identification during large scale variation of wind direction. Indeed, using a longer time interval of data implies that the transition of the wind direction affects the correlation of the power production over a longer period of time and, thus, clusters are identified with a larger time delay.

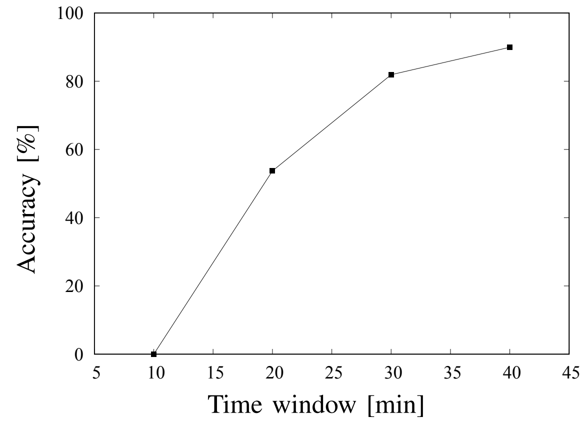

Fig. 6. Accuracy in the identification against the length of time window used for computing the correlation coefficients.

B. Promptness of the response

Given the physical response of the system, the promptness of the response can be divided in two phases:

1) The promptness of algorithm to recognize that wind direction is starting to change, as for example at time $t = 74\ min$ in Figure 3. This ability is particularly desired because a delay in recognizing the transients in changing wind direction would cause most of the turbines in the wind farm to be misaligned respect to the wind direction when no wake steering is actually needed.
2) The time needed to recognize that a new cluster configuration is reached after a change in the wind direction. In this case it is desirable to allow a larger time delay since, in reality, large scale variation in the wind direction can be accompanied by subsequent transients with unstable wind direction. It is then desirable that the algorithm allows a time delay between the formation of the cluster and the identification so that the collective control approach is applied only when the wind direction reaches a new stable condition.

Table I reports the time needed for the algorithm to execute the two tasks during the transition of the wind direction from $\theta = 0°$ to $\theta = 30°$. Three different time windows are considered of respectively 20, 30 and 40 minutes. The time to detect the changing wind direction increases with the length of the time window but remains in the order of about 2 minutes. The time to detect new cluster configuration instead has a minimum for a time window of 30 minutes and then it increases considerably for a time window of 40 minutes. In the case of 20 minutes time window, the time to detect the clusters is higher than the 30 minutes time window because of the reduced accuracy in the identification.

Considering the two criteria (accuracy and promptness) we can conclude that 30 minutes is the best performing time window of data needed to identify turbine clusters or the wind farm configuration considered in this study. Indeed, this time window allows achieving both a good accuracy and promptness during large scale transient of the wind direction.

It should be noted, however, that this time window could vary with the extension of the wind farm.

TABLE I
TIME WINDOW AGAINST PROMPTNESS OF THE RESPONSE.

Time window	Time to detect changing wind direction	Time to detect new cluster config.
20 min	1.4 min	25 min
30 min	1.8 min	20 min
40 min	2.6 min	33 min

VI. CONCLUSIONS

In this study, we presented the application of the cluster identification method developed in [14] applied to the more challenging conditions of time-varying wind direction. Respect to other approaches, the presented cluster identification method is model-free. It requires only the power production signal of the turbines in the wind farm and the estimation of the wind velocity upstream of the wind farm without any assumptions about the wind direction or the turbulent intensity. Yaw control is able to increase the energy production of wind farms by reducing the wake interaction. However, we found that an actual power gain from yaw control is obtained only when the wind direction remains consistent over a prolonged amount of time. Large scale wind direction variations imply not uniform wind conditions across the wind farm and, as a consequence, weaker and not uniform wake interaction within the wind farm. During transients of the wind direction, yaw control may result in power production losses respect to the individual control where all turbines are aligned with the wind direction. Therefore, the wind farm controller should be able to promptly identify variation in the wind direction to avoid power losses due yaw misalignment. The cluster identification methodology based on the correlation of the power production signals is able to correctly identify such wind direction transition with a time delay of few minutes. We also found that the best performing time window of data needed to identify the clusters is 30 minutes long for the current wind farm set up. This time window corresponds to approximately 6 times the minimum amount of time that takes for the wakes to propagate from the most upstream to the most downstream turbines in the wind farm. While this may seem a limitation for very large wind farms, wind condition may spatially vary within the wind farm with an extension of several kilometers. Since the cluster identification algorithm consider the collectively of the turbines to identify the wake interaction, it may be convenient to divide the wind farm in smaller subsets within which clusters are identified. The division of the wind farm in subsets would allow considering spatial inhomogeneity of the wind conditions within the wind farm and reducing the time window needed to compute the correlation among the turbines. However, such application to very large wind farms needs additional effort in terms of both numerical and experimental studies.

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