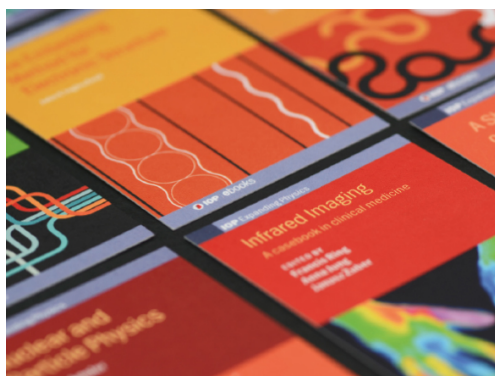


PAPER • OPEN ACCESS

Real-time identification of clusters of turbines

To cite this article: Federico Bernardoni *et al* 2020 *J. Phys.: Conf. Ser.* **1618** 022032

View the [article online](#) for updates and enhancements.



IOP | ebooks™

Bringing together innovative digital publishing with leading authors from the global scientific community.

Start exploring the collection—download the first chapter of every title for free.

Real-time identification of clusters of turbines

Federico Bernardoni, Umberto Ciri, Mario Rotea, Stefano Leonardi

The UTD Center for Wind Energy

Department of Mechanical Engineering, University of Texas at Dallas, Richardson, Texas, USA

E-mail: Stefano.Leonardi@utdallas.edu

Abstract. The implementation of wind farm control strategies requires knowledge of the turbines that are aerodynamically coupled through wake effects. As the wind changes direction, the *clusters of coupled turbines* may vary within the array. The present study proposes a simple method to identify clusters of turbines coupled by the wake interaction. The method uses the correlation of the power production fluctuations of the turbines in the wind farm. Large Eddy Simulations (LES) results of the flow in a 4×4 turbine array have been used to validate the proposed approach. This study introduces a tool which can be integrated into a control system to optimize wind plant power production.

1. Introduction

Turbines in a wind farm do not operate in isolated conditions due to wake interactions. A change in the operation of an upstream turbine may affect the efficiency and the power production of downstream turbines. It is well-known that wake interactions play an important role in the overall power production of a wind farm, and these interactions are likely to change with variations in wind conditions. For example, Clifton et al. [1] reported that the variability of the wind conditions is one of the major causes associated with power losses due to the wake effects, while Porté-Agel et al. [2] showed through Large Eddy Simulations (LES) that a change in the wind direction as small as 10° from the worst-case full-wake condition may increase the total output power as much as 43% for the Horns Rev offshore wind farm. Mortensen et al. [3] estimated an energy loss due to wake interaction between 6% and 10% for two wind farms operating onshore, and between 8% and 14% for two offshore wind farms in the Irish Sea. Barthelmie et al. [4] showed that the power loss of downstream turbines can reach up to 30% in the worst case scenario for the Horns Revs wind farm in Denmark. Although new wind farms layout optimization [5] may mitigate the power losses due to wake interactions, the variability of the wind direction prevents from a complete elimination of such interactions and the associated power losses.

Control strategies have been developed to mitigate the wake interaction and maximize the power production of the farm. Using a data-driven parametric model, Gebraad et al. [6] presented a control strategy based on the yaw control of the upstream turbines. These authors exploited the wake lateral deflection caused by the misalignment between the incoming wind and the rotor plane to steer the wake away from the downstream turbine and thus increase the overall power production of a two-turbine cluster. Fleming et al. [7] investigated strategies to redirect turbine wakes such as yaw and tilt actuation in order to have a more energetic flow impinging on the downstream turbines. Ciri et al. [8] demonstrated using LES the possible reduction of



the power losses using Extremum Seeking Control (ESC) [9] of the yaw angle for a two-turbine cluster. Recent field studies have demonstrated that the application of wake steering control strategies is able to increase the power production of two-turbine clusters up to 4% [10, 11]. In these studies, the wind direction is known and constant, so that turbines that are coupled by the wake interaction, hereafter *turbine clusters*, can be determined a priori and do not change in time. In reality the wind changes direction and therefore the clusters of turbines must be determined in real time. An efficient application of coordinated control strategies requires the detection of the clusters in real time.

The wake direction is mainly affected by the wind direction. Hence, a possible strategy for the identification of the turbine clusters could be based on the geometry of the wind farm and the accurate detection of the wind direction. Since the wind direction may vary within a large wind farm due to atmospheric meso-scale structures and local turbulence, the use of a few isolated external instruments such as meteorological tower or LIDAR scans can lead to erroneous assumptions for the regions of the wind farm that are far from them. To increase the accuracy of the wind direction measurements, Annoni et al. [12] developed a consensus-based approach able to incorporate Supervisory Control And Data Acquisition (SCADA) data from multiple turbines in every region of the wind farm. However, in case of yaw misalignment the wind direction may not be a reliable indicator of the wake direction. Thus, the use of wind direction as the sole indicator for detecting clusters of aerodynamically coupled turbines may not yield accurate results. Hence, it is desirable to develop a tool for the identification of clusters of coupled turbines with the ability to promptly adapt to changes in wind direction and turbine yaw angles.

The present study aims at developing a method to detect clusters of turbines coupled by the wake interaction through the correlations of the power production of each turbine. Instead of using wind direction or speed, the signal quantifying the actual power produced by each turbine is taken into account. An ideal wind farm of 16 wind turbines is simulated using our in-house large eddy simulation code coupled with the rotating actuator disk. The resulting “virtual” SCADA data are then used to correlate the power production of each pair of turbines in the array and determine the clusters of turbines.

Section 2 presents the numerical method employed in the simulations; section 3 gives the the wind farm layout and the definition of turbine clusters; section 4 introduces the method to identify the clusters of turbines; section 5 validates the proposed approach for a specific wind direction; finally, section 6 summarizes the findings of the paper.

2. Computational Setup

The simulations have been performed with our in-house LES code UTD-WF. The filtered non-dimensional governing equations for incompressible flow are:

$$\frac{\partial U_i}{\partial x_i} = 0 \quad (1a)$$

$$\frac{\partial U_i}{\partial t} + \frac{\partial U_i U_j}{\partial x_j} = -\frac{\partial P}{\partial x_i} + \frac{1}{Re} \frac{\partial^2 U_i}{\partial x_j \partial x_j} - \frac{\partial \tau_{ij}^{sgs}}{\partial x_j} + F_i \quad (1b)$$

where U_i is the i^{th} component of the filtered velocity vector, P is the filtered modified pressure, $Re = U_{ref} D / \nu$ is the Reynolds number, ν is the kinematic viscosity, τ_{ij}^{sgs} is the subgrid stress tensor and F_i is the body force that accounts for the effects of the turbines on the aerodynamic field. Details of the numerical code are in Orlandi and Leonardi [13] and Santoni et al. [14]. The forces of the rotor acting on the flow are reproduced using the rotating actuator disk model [9, 15]. The disk rotates in time with the instantaneous rotational speed of the turbine ω

determined through the angular momentum balance between the aerodynamic torque T_{aero} and the generator torque M_{gen} :

$$I\dot{\omega} = T_{aero} - M_{gen} \quad (2)$$

where I is the rotor inertia. The generator torque is determined through a standard region II control law, where the generator torque is taken proportional to the square of the generator speed [16, 17]:

$$M_{gen} = k_{gen} \cdot \omega_{gen}^2 \quad (3)$$

where $\omega_{gen} = N_g \cdot \omega$ is the high-speed shaft angular velocity, N_g the gear ratio ($N_g = 97$). In equilibrium ($\dot{\omega} = 0$), the operating rotational speed is determined by the value of the torque gain k_{gen} . To achieve maximum efficiency the torque gain is taken to be:

$$k_{gen} = \frac{1}{N_g^2} \frac{1}{2} \rho \pi R^5 \frac{C_p(\lambda_{opt})}{\lambda_{opt}^3} = 2.2 \text{ Nm/rpm}^2 \quad (4)$$

where $\lambda_{opt} = 7.5$ for the NREL 5-MW reference turbine, R is the radius of the turbine and C_p is the maximum power coefficient of the turbine. We regard the torque gain in equation (4) as the *baseline design value*.

The computational box in streamwise direction (along the wind direction) and spanwise direction (orthogonal to wind direction) is $24D$ and $19.2D$ respectively. The distance of the first row of turbines from the inlet is $4D$ to minimize numerical reflection of the induction zone [18], while the last row of turbines is at $5D$ from the outlet. The vertical size of the domain is kept constant and equal to $10D$. The grid is stretched in the vertical direction in order to have a finer grid resolution in the region with the turbines. The grid resolution in the region of the turbines is uniform in all directions, $\Delta x = \Delta z = \Delta y = 0.025D$.

No-slip conditions are applied at the bottom boundary of the domain, on the nacelles and the towers of the turbines. Free-slip conditions are applied at the top boundary of the computational domain. Periodic boundary conditions are imposed at the two spanwise sides of the domain and radiative boundary conditions [19] at the outlet. In order to reproduce the atmospheric boundary layer at the inlet, turbulence obtained from a precursor simulation is superimposed to the mean velocity profile:

$$\frac{U}{U_{hub}} = \left(\frac{y}{y_{hub}} \right)^\alpha \quad (5)$$

where y is the vertical coordinate, y_{hub} is the hub height and α is the shear exponent set to $\alpha = 0.05$. The streamwise component of the wind velocity at height y is denoted by U and $U_{hub} = U_{ref}$ is the mean streamwise component of the wind velocity at the hub height. From the superposition of the mean flow of equation (5) and the turbulence from the precursor, the resulting turbulence intensity at the hub height impinging the first row of turbines is equal to 11%.

3. Wind farm layout and definition of turbines clusters

A “digital” wind-farm composed of 16 NREL-5MW reference turbines [20], arranged in 4 rows and 4 columns, is considered. The turbines have a rotor diameter $D = 126$ m, rated wind speed $U_{rated} = 11.4$ m/s and rated power $P_{rated} = 5$ MW. The turbine spacing in the transversal direction (West-East) is $3D$, while in the longitudinal direction (South-North) the spacing is $5D$ (Fig. 1a). The average wind speed at the hub height is equal to $U_{ref} = 0.8U_{rated}$.

A change on the operating condition on one turbine could potentially affect all the other 15 turbines. To illustrate the concept we performed a numerical experiment. All turbines of the

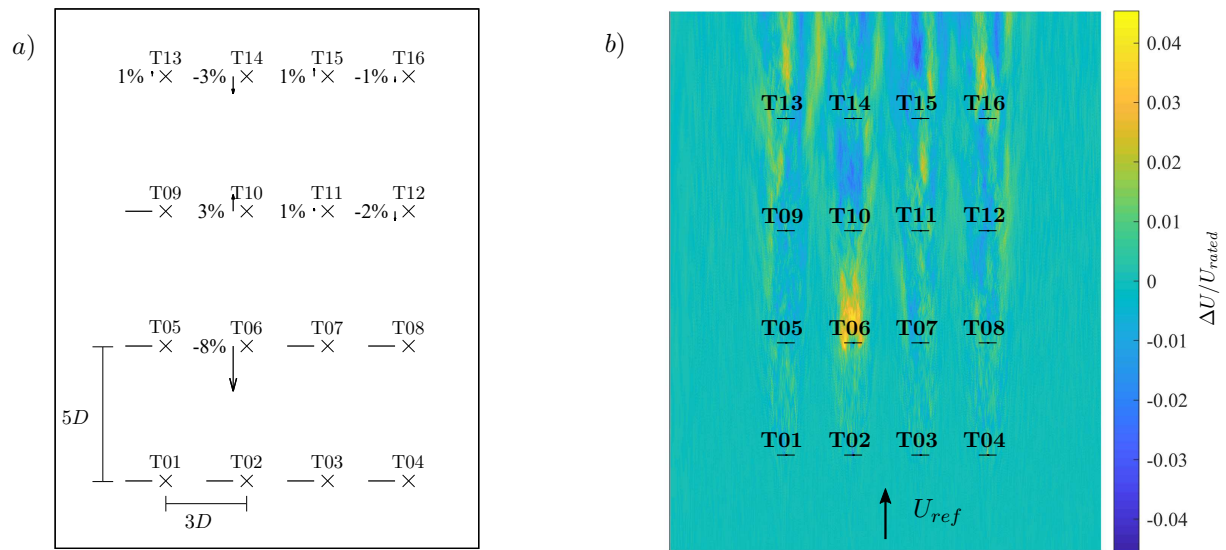


Figure 1. a) Variation of the power production due to the 45% increase of T06 torque gain; horizontal solid lines indicate that the power variation is less than 1%. b) Difference between the time-averaged field at the hub height when T06 torque gain is increased of 45% and the time-averaged field when all turbines operate at the optimal torque gain.

wind farm operate at their optimal torque gain (baseline case). The torque gain of turbine T06 is instantaneously increased by 45% with respect to the baseline; T06 was chosen because it is located close to center of the wind farm and consequently it can potentially affect a larger number of turbines. However, the same experiment could be repeated with other turbines. An increase of torque gain, for a constant incoming velocity leads to a decrease of the angular speed of the turbine, reduction of the TSR (tip-speed ratio) and then of the power production (−8% as shown in Fig. 1a). Due to the non-optimal torque gain imposed to T06 the momentum (or energy) extracted by this turbine is smaller and consequently the mean velocity of its wake is larger. Figure 1b shows the difference of the time-averaged velocity field at the hub height between the case in which the torque gain of T06 is increased and the baseline case. A more energetic flow impinges on T10 leading to the 3% increase of its power production. Conversely, T14 faces a slightly slower flow with respect to the baseline case (Fig. 1b) and it produces less energy. Smaller variations of the power production are experienced by other turbines that are not directly downstream of T06 (Fig. 1a). Given the elliptical nature of the governing equations, the presence of free-stream turbulence and wake instability phenomena such as wake meandering can cause the propagation of a disturbance in spanwise direction. When a variation of the angular speed of a turbine is imposed, the interaction of its wake with the free-stream turbulence may change with a consequent propagation of the disturbance to turbines not aligned with the wind direction. Upstream turbines are very weakly influenced by a change on a downstream turbine. In fact, despite the equations are elliptic in space, the convective terms dominate over the diffusive terms, and the equations are almost parabolic lending justification to the dynamic programming of Rotea [21].

The variation of power production for turbines outside the wake of the upwind turbine is smaller and it is highly dependent on the turbulence intensity. Turbines affected significantly by a change in the operating conditions of another turbine can be defined to belong to the same “cluster”. On the other hand, a perturbation to a turbine belonging to a particular cluster, to a reasonable approximation, does not influence turbines belonging to a different cluster.

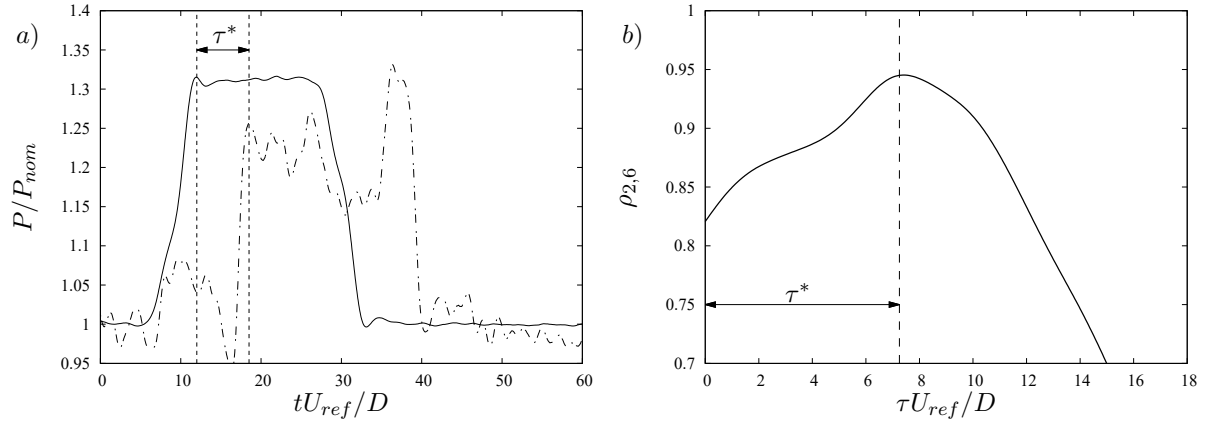


Figure 2. a) Percentage variation of the power, P , respect to the nominal power, P_{nom} , when the inlet velocity is increased by 10%: — T02, - - - T06. b) Power correlation coefficient between T02 and T06. τ^* is the time the wake takes to propagate from T02 to T06.

4. Identification of turbine clusters

In this paper we propose an approach based on each turbine's response to wind velocity fluctuations in the incoming wind. The wind velocity impinging the turbine rotor, and as a consequence the power production of the turbine, fluctuates in time. Because turbulence is, to a good approximation, transported by the wake (Taylor hypothesis), we expect that turbines belonging to the same cluster (i.e., in each others wakes) would have highly correlated power time series.

To test this hypothesis we performed a numerical experiment. Assume the wind farm is at steady state with each turbine working in ideal conditions. Let us increase the inlet velocity in front of T02 (see Fig. 1) by 10% for about 20 non-dimensional time units and then reduce it to its original value.¹ Because the inlet is at a distance of $4D$ from the first row of turbines, after $t \simeq 4D/U_{ref}$, the wind with increased momentum starts impinging on T02 (see Fig.2). The aerodynamic torque increases, and the turbine adjusts its rotor angular speed to a higher value. The power production, which is proportional to the cube of the incoming velocity $P \simeq \frac{1}{2}\rho U_{ref}^3 C_p A$, increases by about 30% (due to the 10% increase in wind speed). The wake of T02 has also more energy because of the increased inlet wind speed, and when it reaches T06, the power production increases too, about 20 – 25%. The increase of power in the two turbines does not occur at the same time but there is a delay τ^* between the instants at which the power rises due to the time it takes for the wake to propagate from T02 to T06 (Fig.2a).

Let us evaluate the correlation between the power time series corresponding to T02 and T06. The correlation coefficient of the power production of each pair (r, s) of turbines is defined as

$$\rho_{r,s}(\tau) = \frac{\sum_{i=1}^N (P_r(t_i) - \overline{P_r}) (P_s(t_i + \tau) - \overline{P_s})}{\sqrt{\sum_{i=1}^N (P_r(t_i) - \overline{P_r})^2 \sum_{i=1}^N (P_s(t_i + \tau) - \overline{P_s})^2}} \quad (6)$$

where t is time and τ is the correlation time lag. The number of time samples is denoted by N , which is also the number of samples used to calculate the time-averaged quantities (denoted with overlines), and P_j denotes the power production of the j^{th} turbine.

Figure 2a shows that it takes about $\tau^* = 7$ non-dimensional time units for the wake to propagate between the aerodynamically coupled turbines T02 and T06. Figure 2b shows that

¹ The non-dimensional time is defined as tU_{ref}/D , where t is the dimensional time in seconds.

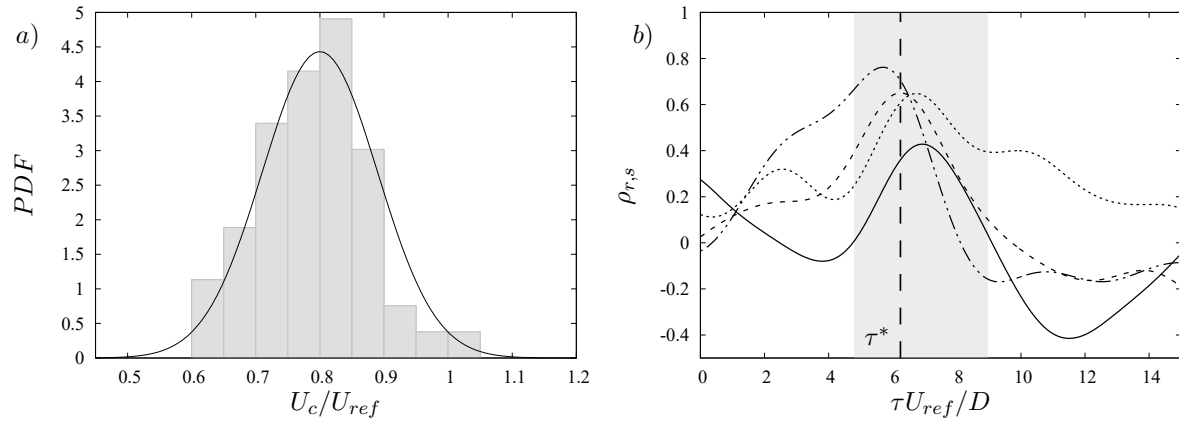


Figure 3. a) PDF of the ratio between the convection velocity U_c and the free-stream velocity U_{ref} . The histogram of the PDF is shown with grey bars, while the solid line is the best-fit normal distribution with mean value $\mu_U = 0.8$ and standard deviation $\sigma_U = 0.09$. b) Power correlation coefficient variation with time lag, τ , for the turbine pairs in the second and third rows. — T05-T09, ---- T06-T10, T07-T11; -.-.- T08-T12.

the correlation coefficient between these two turbines is maximized at $\tau^* = 7$, approximately. This simple example suggests that *turbine pairs with high correlation coefficients belong to the same cluster*.

It should be noted that large coherent turbulent structures in the incoming wind can induce correlation in the power production of turbines that do not belong to the same cluster. The detection of such coherent flow structures is extremely difficult to perform in real time. Given the random nature of the turbulence, their contribution to the power correlation is filtered out when very long time-series of data are taken into account (very large value of N in eq.(6)). For practical applications in real-time it is unfeasible to use long averaging times. For this reason, the following analysis uses 30 minutes of power production data ($N \simeq 2800$ in this set of simulations). Note that moving averages of finite duration can be employed to track cluster variations over time, as long as the time window allows real-time computation of correlation coefficients. In order to filter out large coherent turbulent structures, the physical properties of the wake can be used. Given the transport of turbulence in the wake [22], the correlation should be maximum for a time lag τ^* , which is the time a disturbance on the upstream turbine takes to reach the downstream turbine. The time lag can be calculated as $\tau^* = d/U_c$, where d is the distance between the turbines and U_c is the convection velocity, which can be thought as the average velocity at which a disturbance travels in the wake from the upstream to the downstream turbine.

The convection velocity depends on the momentum deficit at the turbine, i.e. the thrust coefficient. We computed the convection velocity for a large database of cases. Fig. 3a shows the Probability Density Function (PDF) of the ratio U_c/U_{ref} . The gray bars represent the PDF obtained from the simulations while the solid black line is the best-fit normal distribution. As an example, Fig. 3b shows the plot of the correlation coefficient for 4 pairs of turbines separated by a distance of $5D$ (site specific values of the convection velocity may be calculated using the power and wind velocity from SCADA). We found that, in design condition, it can be assumed $\mu_U = U_c/U_{ref} \simeq 0.8$ with a standard deviation of $\sigma_U = 0.09$. This is consistent with Ciri et al.[23] who found $U_c \simeq 0.7U_{ref}$.

The shadowed area in Fig. 3b corresponds to the time-lag interval where the peaks of correlation are expected to occur. A high correlation occurring for a time delay outside the

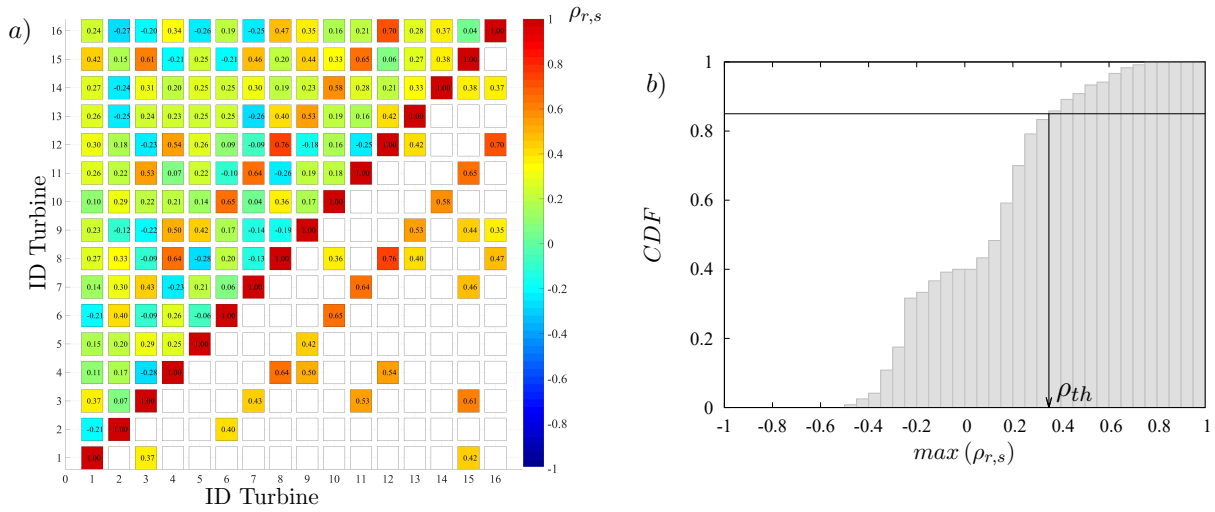


Figure 4. a) Power correlation coefficients for each pair of turbines. The matrix cells below the diagonal show only the values $\rho_{r,s} > \rho_{th}$ to filter out turbulent coherent structures. b) CDF of the maximum peak values of the correlation coefficients with 0° wind direction; the solid black line denotes the threshold ρ_{th} for detecting coupled turbine pairs; in this case 15% (1-0.85).

shadowed area is unlikely to be due to wake interaction but rather to coherent structures in the flow. Therefore, by computing the correlation coefficient in Eq.6 only for time delay in the interval $\tau \in [d/((\mu_U + 3\sigma_U)U_{ref}), d/((\mu_U - 3\sigma_U)U_{ref})]$ we filter out all the coherent structures in the atmospheric boundary layer with a time scale different than τ^* , and eliminate possible outliers, i.e. turbines coupled not through the wake but because of the coherence in the incoming flow.

5. Application of the correlation-based method to detect turbine clusters

The correlation coefficient of the power production of each pair of turbines has been calculated and shown in the cells above the diagonal of the matrix in Fig. 4a where the coordinates of the cells correspond to the pair of turbines. The value in the cell is the correlation coefficient between the two turbines (e.g., the number in cell 3-5 is the correlation coefficient between turbines T03 and T05). As discussed in the previous section, turbines correlated through the wake have a positive correlation (Fig. 2b), i.e. both turbines either increase or decrease the power production.

It can be assumed that the correlation associated with the wake interaction is higher than the one due to the remaining turbulent coherent structures (not filtered by τ^*). In fact, a turbine is in the wake of another until the wind changes direction. On the other hand, very large turbulent coherent structures have random orientation, meander and are not persistent in a particular position as the wakes. As a consequence, two turbines are affected by the same turbulent structure for a much shorter time than those in each other wake.

For the practical identification of the clusters, a threshold value of correlation, ρ_{th} can be set: pair of turbines with a correlation greater than the threshold are more likely to be coupled by the wake. The value of the threshold ρ_{th} may vary with the wind direction. When the wind direction changes, the distance between two turbines coupled by the wake changes (by a factor $1/\cos\theta$ with respect to the $\theta = 0^\circ$ reference case). The threshold is also expected to vary according to the wind farm layout; a one-time tuning will be then required for each different wind farm. Because of the viscosity and turbulent transport, the correlation between the two power signals is expected to decrease by increasing the distance between the turbines. Hence,

a different threshold value has to be determined for each wind direction. In order to provide a general procedure, ρ_{th} is determined such that the Cumulative Distribution Function (CDF) of peak correlation coefficients is 0.85 at ρ_{th} . *This means that only the highest 15% correlation coefficients are considered as indicative of turbine pairs.*

Figure 4b reports as an example the CDF associated with 0° wind direction. The figure shows the percentage of pairs of turbines that exhibit a correlation maximum value smaller than the one associated with each bin. The threshold value is $\rho_{th} = 0.35$ since the bin associated with this value is the first that exceeds a CDF value of 0.85. Different thresholds have been tested. Larger values would discard pair of turbines in each others wake, smaller values would potentially lead to many outliers with correlation due to the turbulence in the wind.

The lower portion of the matrix in Fig. 4a shows the correlation coefficients such that $\rho_{r,s} > \rho_{th}$. Those cells represent the pairs of turbines that are strongly correlated in the time window considered. By drawing a link between each pair of turbines, the clusters can be identified (Fig. 5a).

Color contours of the time-averaged streamwise velocity obtained from the LES (Fig. 5b) are used as benchmark to validate the clusters in Fig. 5a. With some approximation the clusters identified by the proposed strategy are in agreement with those identified through the flow visualization. The pairs of turbines of the 2nd, 3rd and 4th rows in wake conditions show a higher correlation than the pairs in the 1st and 2nd rows. A dominant direction of the links is evident from Fig. 5a; however, outliers indicated by red lines are present.

Another physical property of the wakes can be used to eliminate these outliers. The wakes are aligned with the wind direction, or in case of yaw misalignment, are within $\pm 10^\circ$ (larger misalignment would be unreasonable due to the penalty in power production, see Ciri et al. [8]). Typically, the wind direction does not change much locally within a sector of a farm; thus, the wakes (and links) should all be within $\pm 10^\circ$ degrees of a particular direction. Each link of Fig. 5a corresponds to a particular direction which can be easily calculated from the knowledge of the coordinates of the turbines. We counted the number of links in each 10° sector. Then, we computed the PDF of the link directions dividing the number of links in each 10° sector by the total number of the links in Fig. 5a, i.e. 26, and normalizing with the bin width, i.e. 10. The PDF of the link directions should indicate the most probable wake direction as shown in Fig. 5c. An evident peak is obtained for the link direction $\theta_L = 0^\circ$. Therefore, only the pairs of turbines that are in the direction $\theta = 0^\circ \pm 10^\circ$ can be considered coupled by the wake interaction while all the other pairs are correlated by other causes such as free-stream turbulence.

Applying this criteria a new network is obtained (Fig. 5d) which agrees very well with the flow visualization benchmark. The only erroneous classification is the pair T01-T05 that is not detected by the proposed approach.

Summarizing, the following three criteria are used to determine clusters of turbines:

- (i) a correlation maximum must be calculated for the expected time lag interval $\tau \in [d/((\mu_U + 3\sigma_U)U_{ref}), d/((\mu_U - 3\sigma_U)U_{ref})]$;
- (ii) the value of the maximum must be greater than the threshold value ρ_{th} with $CDF(\rho_{th}) = 0.85$;
- (iii) the direction of the links between the turbines has to be within $\theta_p \pm 10^\circ$ with θ_p the most likely wake direction.

6. Conclusions

A LES study of an ideal wind farm has been performed in order to demonstrate and validate a strategy for the real-time identification of clusters of turbines coupled by wake interactions. It was shown that the clusters can be identified using the correlation in time of the power production of every turbine and exploiting information of the wake propagation time from upstream turbines

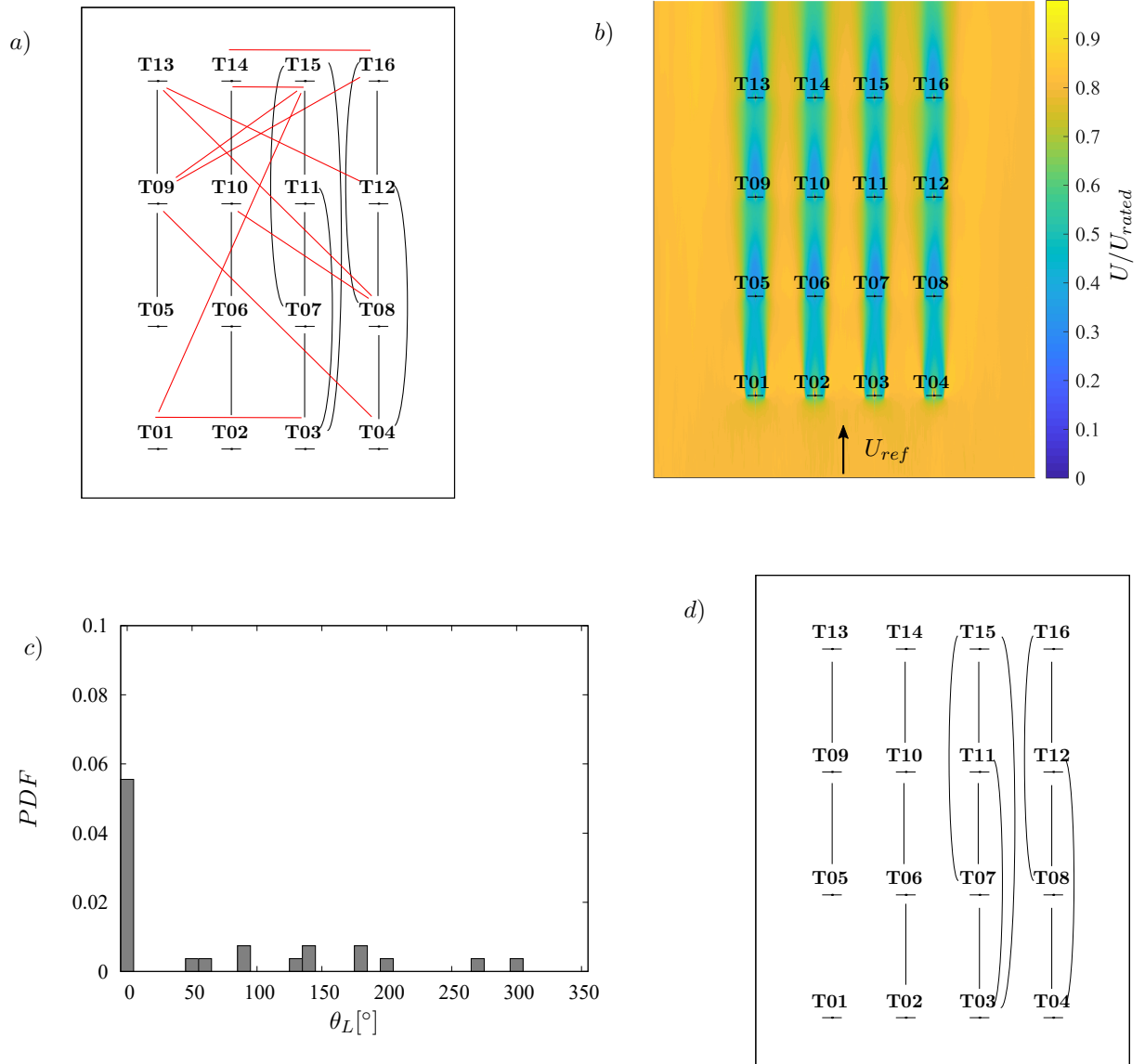


Figure 5. *a)* Network of coupled turbines that have a non-zero correlation under the diagonal of Fig. 4a; red lines correspond to erroneous classifications. *b)* Color contours of the time averaged streamwise velocity at the hub height. *c)* PDF of the directions associated to the links (θ_L) of the network. *d)* Network of turbines that are found to interact though their wake with the proposed approach.

to the downstream ones. The magnitude of the correlation peak can be also used as an indicator of the intensity of the wake interaction. That is, the larger the peak, the more intense is the wake impinging on the downstream turbine. It should be noted that strong turbulence in the free-stream flow can lead to false classification of clustered turbines for the most upstream rows of the wind farm. In order to overcome this issue, the wake direction can be estimated using the same correlation data and exploiting the known geometrical layout of the wind farm. The peak of the PDF identifies the direction in which most of turbine pairs interact, that is to some approximation the wake direction. Hence, all the pairs that have a high correlation peak but are not aligned with such direction can be disregarded.

From the study of the propagation of an imposed disturbance it was found that only the consecutive downstream turbine is strongly affected by the wake of the upstream turbine. Turbines that are further downstream or that do not belong to the same cluster can be affected by operational changes of a single upstream turbine but the presence of free-stream turbulence may cause this effect to be highly uncertain. Thus, clusters of two turbines can be considered as minimal control unit for the application of coordinated control approach.

It is our intention to further develop the study by performing a simulation in which the wind direction is varied in time detecting the clusters of turbines with a running average of the last 30 minutes of data. The proposed procedure is thought to be applied by using available SCADA data such as power production signal in time without assuming an a priori wind direction. The low computational cost needed for the computation of correlation coefficient allows the real-time evaluation of the clusters for a more tailored application of wind farm control strategies.

Acknowledgments

This research was partially supported by NSF Award No. 1839733 from the CMMI division of ENG directorate.

References

- [1] Clifton A, Smith A and Fields M 2016 Wind plant preconstruction energy estimates: Current practice and opportunities Tech. Rep. NREL/TP-5000-64735 NREL - National Renewable Energy Laboratory Golden, Co, USA
- [2] Porté-Agel F, Wu Y T and Chen C H 2013 *Energies* **6** 5297–5313
- [3] Mortensen N G, Nielsen M and Ejlsing Jørgensen H 2015 EWEA Annual Event and Exhibition 2015 (European Wind Energy Association (EWEA))
- [4] Barthelmie R J, Hansen K S, Frandsen S T, Rathmann O, Schepers J G, Schlez W, Phillips J, Rados K, Zervos A, Politis E S and Chaviaropoulos P K 2009 *Wind Energy* **12** 431–444
- [5] Padrón A S, Thomas J, Stanley A P J, Alonso J J and Ning A 2019 *Wind Energy Science* **4** 211–231
- [6] Gebraad P M O, Teeuwisse F W, Van Wingerden J W, Fleming P A, Ruben S D, Marden J R and Pao L Y 2014 *Wind Energy* **19** 95–114
- [7] Fleming P A, Gebraad P M O, Lee S, van Wingerden J W, Johnson K, Churchfield M, Michalakes J, Spalart P and Moriarty P 2014 *Renewable Energy* **70** 211–218
- [8] Ciri U, Rotea M A and Leonardi S 2018 *Wind Energy* **21** 1395–1405
- [9] Ciri U, Petrolo G, Salvetti M V and Leonardi S 2017 *Energies* **10(6)** 821
- [10] Fleming P, Annoni J, Shah J J, Wang L, Ananthan S, Zhang Z, Hutchings K, Wang P, Chen W and Chen L 2017 *Wind Energy Science* **2** 229–239
- [11] Fleming P, King J, Dykes K, Simley E, Roadman J, Scholbrock A, Murphy P, Lundquist J K, Moriarty P, Fleming K *et al.* 2019 *Wind Energy Science* **4** 273–285
- [12] Annoni J R, Bay C, Johnson K E, Dall’Anese E, Quon E W, Kemper T W and Fleming P A 2019 *Wind Energy Science (Online)* **4**
- [13] Orlandi P and Leonardi S 2006 *Journal of Turbulence* **7** 1–22
- [14] Santoni C, Ciri U, Rotea M and Leonardi S 2015 *2015 American Control Conference (ACC)* (IEEE) pp 1715–1720
- [15] Ciri U, Salvetti M V, Carrasquillo K, Santoni C, Iungo G V and Leonardi S 2018 *Direct and Large-Eddy Simulation X* (Springer) pp 109–115
- [16] Johnson K E, Pao L Y, Balas M J and Fingersh L J 2006 *IEEE Control Systems Magazine* **26** 70–81
- [17] Laks J H, Pao L Y and Wright A D 2009 *2009 American Control Conference (ACC)* (IEEE) pp 2096–2103
- [18] Santoni C, García-Cartagena E J, Ciri U, Zhan L, Iungo G V and Leonardi S 2020 *Wind Energy* **23** 691–710
- [19] Orlanski I 1976 *Journal of Computational Physics* **21** 251–269
- [20] Jonkman J, Butterfield S, Musial W and Scott G 2009 Definition of a 5-mw Reference Wind Turbine for Offshore System Development Tech. Rep. NREL/TP-500-38060 NREL - National Renewable Energy Laboratory Golden, CO, USA
- [21] Rotea M A 2014 *IFAC Proceedings Volumes* **47** 3639–3644
- [22] Townsend A 1976 *The structure of turbulent shear flow* (Cambridge University Press)
- [23] Ciri U, Rotea M and Leonardi S 2017 *Renewable Energy* **113** 1033–1045