Correlations of power output fluctuations in an offshore wind farm using high-resolution SCADA data

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DOI: 10.5194/wes-2020-96

Authors response to referee comments

Dear referees, we appreciate the constructive comments which help to improve our paper. Below we will discuss all comments in detail.

Authors response to comments from referee #1

RC1 ** In the abstract it is unclear what "clustering algorithm k-means" is. This method may not be known to all readers and requires explanation. * Even after reading the entire manuscript the goal and exact outcome of this analysis remains vague. It seems that during this analysis the data is sorted, based on the power fluctuations, and that based on this division the power correlations in certain parts of the data are more pronounced than in other parts of the data set. What does this tell us exactly? I guess from figure 8 and 9 we can see that power correlations are more pronounced for certain turbines than for others (however, data from the same turbines seems to be included in different clusters). So in figure 8 cluster 5 is dominated by turbines on the first row, but a similar observation can be made from figure 6a already. So it is not quite clear what the added value of the "For wind directions approaching 0° and 180° the wind turbines in a pair are oriented more perpendicular to the wind and fluctuations reach both wind turbines A and B at nearly the same time.-means clustering algorithm" analysis in this work is. This should be clarified, or that analysis should be removed from the manuscript.*

AC: Thank you for pointing this out. Fig. 6 shows that the position of the wind turbine pairs has an influence on the correlation of their power output fluctuations and that the correlation curves are more pronounced for wind turbine pairs at the back of the wind farm. However, the presented curves are averages of several correlation states which depend on the flow conditions the wind turbine pairs are exposed to. Combining the introduced parameters: the standard deviation of the power output fluctuations and the power difference of the wind turbines in a pair, with the clustering algorithm For wind directions approaching 0° and 180° the wind turbines in a pair are oriented more perpendicular to the wind and fluctuations reach both wind turbines A and B at nearly the same time.-means, the data can be separated according to the underlying correlation states, independently from the position of the wind turbines. The clusters with the highest correlations mostly consist of wind turbine pairs at the back of the wind farm. Their correlation is significantly increased compared to the average power output fluctuation correlation of all pairs in the last row of the wind farm. We revised the abstract and introduction to clarify the added value of the *k*-means clustering algorithm:

> p.1, ll.1f: Space-time correlations of wind turbine pairs provide information on the flow conditions within a wind farm and on the interactions of the wind turbines. Such information plays an important role for the control of wind turbines and short-term load or power forecasting. However, the challenge to analyse space-time correlations of power output fluctuations of wind turbine pairs in a free field wind farm are the highly varying flow conditions. Here, we present an approach to investigate space-time correlations of power output fluctuations of wind turbine pairs in free field based on high-resolution SCADA data, which overcomes the challenge of highly variable flow conditions within the wind farm. Using eight months measurements from an offshore wind farm with 80 wind

turbines, the influences of different parameters on the correlation of power output fluctuations are analysed. Wind direction investigations show that correlations of power output fluctuations of wind turbine pairs are highest for streamwise aligned pairs and decrease towards spanwise pairs. Further, it is found that the correlation of power output fluctuations of streamwise aligned wind turbine pairs depends on the location of the wind turbines within the wind farm as well as the inflow conditions (free-stream or wake). The main outcome is that the correlation of streamwise aligned wind turbine pairs can be characterised by the standard deviations of the power output fluctuations and the power difference of the wind turbines in a pair. Evaluating these parameters with the data-driven clustering algorithm *k*-means, wind turbine pairs with similar power output fluctuation correlations are grouped depending on these parameters and independent from their location. These groups are here referred to as correlation states. With this approach we account for the highly variable flow conditions inside a wind farm which influence the correlations in an unpredictable way. As a final result we shows that these parameters lead to clearly distinguishable correlation states.

p.2, ll. 56f: In our work, we analyse 1 Hz wind farm SCADA data to describe space-time correlations of power output fluctuations of wind turbine pairs. In contrast to the wind tunnel measurements by Bossuyt et al. (2017a) and the LES analysis by Lukassen et al. (2018) mentioned above, the data set processed here includes unstable inflow conditions, dynamically operating wind turbines as well as changing flow conditions within the wind farm. Furthermore, there may be potential measurement inaccuracies. The result is a large and highly complex data set. In this paper we investigate the influencing factors on the correlation of power output fluctuations of wind turbine pairs and introduce parameters to distinguish different correlation curves, here called correlation states.

RC2 *Line 15: "7 wind farms were connected to the grid"? ==> This seems low. I guess only wind farms above a certain size are included.*

AC According to WindEurope, 7 wind farms were fully grid-connected and additional 3 have been partially connected to the grid. Furthermore, the construction of 5 other wind farms started (Ramírez et al., 2020). For clarification we added the information that this number refers only to grid-connected wind farms:

p.1 ll. 20f: Considering offshore wind power in 2019, the capacity in Europe has increased by 3.627 GW, and a total of 7 wind farms were fully connected to the grid, while the average size of wind farms increased to 621 MW (Ramírez et al., 2020).

RC3 *Line 47: It seems a bit strange that wind direction changes have only a little effect on power output fluctuations. In fact, I would say that the results presented in the current manuscript indicate the opposite. What kind of wind farm did Dai et al. (2017) considered?*

AC Dai et al. (2017) investigated the influence of wind direction fluctuations around a mean wind direction on the power output fluctuations of single wind turbines. Whereas we investigate the influence of different wind directions on the correlation of wind turbine pairs. We analyse wind different wind direction intervals with a size of 20° and show that different wind directions have an influence on the correlation of the wind turbine pairs. For wind directions around 90° and 270°, the wind turbines of the considered pairs are streamwise aligned to the wind direction and show a high correlation. Whereas for 0° and 180° the wind turbines of a pair are parallel to the wind direction and show nearly no correlation.

Thus, it is correct that the wind direction has an influence on the correlation of the considered wind turbine pairs, but the influence of wind direction fluctuations was not further investigated here. To clarify this, we changed the following texts:

p. 2 , ll. 51f: Dai et al. (2017) analysed 1 Hz wind farm SCADA data with respect to the influence of wind speed fluctuations and wind direction fluctuations on wind turbine power output fluctuations of single wind turbines. They showed a direct relation between wind speed fluctuations and power output fluctuations in the partial load regime.

p. 3, ll. 92f: The nacelle based wind direction φ is estimated based on the measurements of two 2D sonic anemometers installed behind the rotor of each wind turbine. These measurements have to be treated with care as the measured flow behind the rotor is disturbed by the rotation of the rotor and the nacelle itself. Thus, it is only an estimation of the wind direction and yaw of the wind turbine. However, as shown by Dai et al. (2017), wind direction fluctuations at reasonable yaw angles ($< 45°$) have only little effect on the power output fluctuations of wind turbines and thus inaccuracies in φ have no major influence on the performed analysis. The combined measurements of θ_i and φ_i define the wind direction Φ_i at the i-th wind turbine.

RC4 *Line 76: It is stated that U is not measured, but calculated from the measured power. Please clarify how exactly that is done, and to what degree this procedure could affect the presented findings.*

AC Unfortunately, U is provided as a variable within the data set. It is not measured but directly related to the measured power and reconstructed from the wind turbine (controller) settings. Details on the reconstruction are not available. Depending on U, the correlation curves stretch or shrink (see p.6, eq. 3). Thus, if the recalculated wind speed differs from the actual wind speed, the normalised correlation curve might be slightly shifted to a larger τ_{norm}. However, U affects the normalisation of the correlation curves in a consistent manner for all wind turbines. For this reason, we consider U as reasonable variable in the context of this analysis. We revised the description of U and added how it affects the normalisation of correlation curves:

p. 3, ll. 81f: The processed signals include the generated power P, the azimuth angle of the wind turbines (i.e. the nacelle direction) θ, the nacelle based wind direction φ (measured relative to θ), the pitch angle β of each blade, and a reconstructed wind speed U.
The reconstructed wind speed U is not directly measured but provided as a variable which results from the measured power and control variables of the wind turbine. Due to that, U is considered as an approximated and idealised value which does not include wind speed independent power reduction, e.g. by misalignment of the wind turbine due to measurement errors of the wind direction. In the context of this work, it can still be used for assessing the effect of the wind speed on the correlations of power output fluctuations of wind turbine pairs which is further discussed in Sect. 2.2.

p.7, ll. 179f: As mentioned before, U_B is reconstructed and might differ from the actual wind speed affecting the wind turbines. However, in the context of this normalisation the effect on the resulting correlations curves is marginal as the correlation curves may only be slightly shifted due to the deviation to the real wind speed.

RC5 *Line 78: "However, it can still be used for assessing the effect of the wind speed on the wind turbine." ==> what effect of the wind speed on the wind turbine are you referring to (you use the power to get the wind speed).*

AC Thank you for this remark. It should have said the influence of the wind speed on the correlation of power output fluctuations of wind turbine pairs. We corrected this sentence in the context of **RC4** as follows:

p.3, ll. 87f: In the context of this work, it can still be used for assessing the effect of the wind speed on the correlations of power output fluctuations of wind turbine pairs which is further discussed in Sect. 2.2.

RC6 *Figure 1: Throughout the manuscript the authors focus on the 90 degree and 270degree wind directions. Figure 1 suggests the wind farm is not perfectly aligned with the 270 / 90 degree direction (for example turbine 15 seems a little lower than turbine9). Is this indeed the case, and if so, why did the authors not select the wind directions corresponding to the wind farm alignment in the red box of figure 1.*

AC It is correct, that wind turbine 15 and wind turbine 9 are not exactly horizontally aligned. However, we chose to stick wind wind directions 90° and 270° since the best correlation of power output fluctuations were found for these directions as shown in Fig. 3. Also, as we consider wind direction intervals of 20° around 90° and 270°, the 'ideal' wind direction for the slightly horizontal misaligned wind turbines is included within the intervals around 90° and 270°.

RC7 *Table 1: Is the filtering really performed with "no yawing", or is this also practically implemented with some low threshold?*

AC Yes, this filtering is performed with "no yawing" within the considered correlation intervals. This means both wind turbines were not allowed to yaw. To clarify this, we changed the table entry to:

p. 5, Tab. 1:

Signal	Power	Pitch	Yaw
Settings	$0.5\ \mathrm{MW} \leq P \leq 4.5\ \mathrm{MW}$	$\beta < -1.3°$	$\theta = const.$

RC8 *Line 108-111: Please clarify what you mean? Do you refer to turbines which are limited in production because of other consideration than their own individual controller?*

AC With derated wind turbines we refer to wind turbines whose controller settings have been manually changed so that the maximum power is limited to a certain value lower than the nominal power. This means derated wind turbines start pitching earlier than non-manipulated wind turbines as their maximum power limit is reached at lower wind speeds. To clarify this, we revised the text as follows:

p. 5, ll. 119f: The previously defined, limited power range still includes derated wind turbines. For derating wind turbines, their controller is manually changed so that their maximum power is limited to a certain value lower than their nominal power. Due to that, wind turbines might start pitching already in the previously defined load range as their newly set power limit is reached already at lower wind speeds. Hence, to fully exclude pitching wind turbines, the data is filtered for any pitching activity. Please note that for this specific data set this implies that $\beta < -1.3°$.

RC9 *Line 163-165: in the explanation of τ_{norm} you refer to some time averages. What time averages do you exactly use (over the 600 time second window)?*

AC When calculating τ_{norm} for a certain correlation time interval of 600 s starting at time t, we average the reconstructed wind speed at wind turbine B over 300 s for t in the discretised interval $[t_j, t_j + 299\ \mathrm{s}]$ with $\langle U_B(t+\tau)\rangle_{\Delta t_{300}}$, the discretised interval of $U_B(t+\tau)$ e.g. for $\tau = 100$ is $[t_j + 100, t_j + 100 + 299\ \mathrm{s}]$. We corrected eq. 3, removed eq. 4 and revised the paragraph as follows to clarify the procedure:

p. 6, ll. 166f: Similar to Taylor's hypothesis (Taylor, 1938) we assume that depending on the wind speed, wind structures responsible for power output fluctuations measured at an upstream wind turbine A, take some time to travel the distance to the downstream wind turbine B. Hence, to compare correlations at different wind speeds and different wind turbine distances, the time lag τ is normalised for each time interval starting at t_j individually

$$\tau_{norm,intv} = \tau \cdot \frac{\langle U_B(t+\tau)\rangle_{\Delta t_{300}}}{x_{AB}} \tag{3}$$

where $\tau_{norm,intv}$ is the normalized time lag, $\langle U_B(t+\tau)\rangle_{\Delta t_{300}}$ is the average reconstructed wind speed from a certain (downstream) wind turbine B for a time interval $\Delta t_{300} = 300$ s for t in the discretised interval mbox$[t_j, t_j + 299$ s$]$ and a certain lag τ. This means for a certain τ, the averaging interval of $\langle U_B(t+\tau)\rangle_{\Delta t_{300}}$ is $[t_j + \tau, t_j + \tau + 299$ s$]$. x_{AB} is the distance between wind turbine A and wind turbine B.
Due to this definition of $\tau_{norm,intv}$ and τ_{norm} (see Eq. 4), the peak of the correlation curves is expected to be found at $\tau_{norm} = 1$ if the advection speed of the wind speed fluctuations matches the wind speed affecting B. Thus, in partial load situations where wind turbine B is in the wake of wind turbine A, the peak is expected to be at $\tau_{norm} > 1$. Here, the reduced wind speed in the wake recovers slowly, so that the wind speed affecting wind turbine B, i.e., U_B is already partly recovered and hence larger than the advection speed of the fluctuations. As mentioned before, U_B is reconstructed and might differ from the actual wind speed affecting the wind turbines. However, in the context of this normalisation the effect on the resulting correlations curves is marginal as the correlation curves may only be slightly shifted due to the deviation to the real wind speed.
In a next step, the correlation curves with the normalised lag $\tau_{norm,intv}$ are discretised using a histogram with a reference time lag of

$$\tau_{norm} = \tau \cdot \frac{U_{max}}{x_{AB,mean}} \tag{4}$$

where τ is the time lag (0 s to 300 s), U_{max} is an artificially introduced velocity which has to be at least equal to the maximum possible wind speed to fit all normalised curves (here $U_{max} = 13\ \mathrm{ms}^{-1}$). $x_{AB,mean}$ is the average distance between wind turbine A and wind turbine B of the considered wind turbine pairs. Note that $\tau_{norm,intv}$ is only used for stretching and shrinking of the correlation curves and that τ_{norm} is used only for binning of the stretched or shrunk correlations.

p. 7, ll. 195f: In the following, we average correlations over a wind direction interval of 20° and all available time intervals of the considered wind turbines (either all wind turbines or a selection of wind turbines). The averaged correlation is noted as $R(\tau_{norm})$.

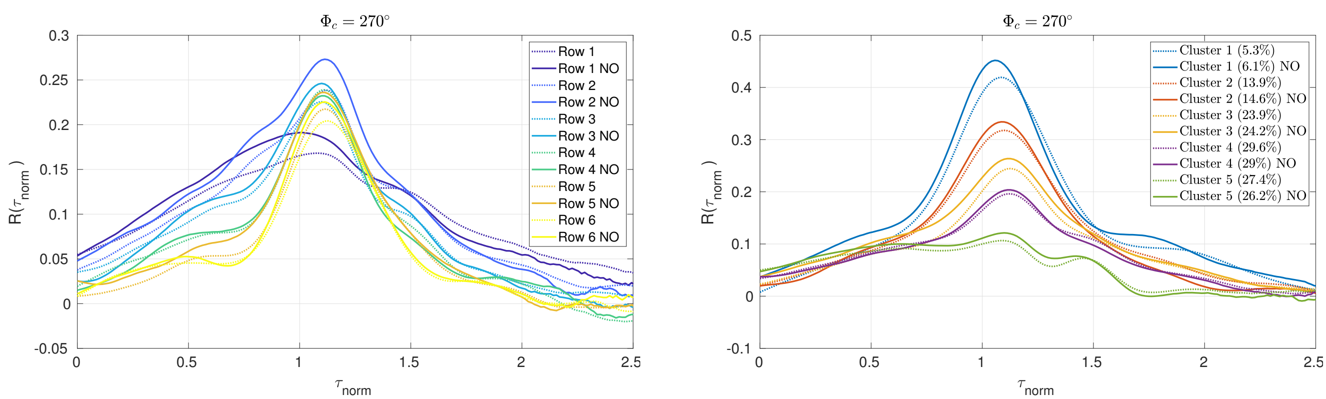
RC10 *Line 171: Why is this reference speed chosen and not a higher value? In figure 4 we see the peak values are observed at t_{norm}=1.1 to 1.2. Can you give some more detailed consideration as what we can infer from this value.*

AC As described in Eq. 4 in the revised Sect. 2.2 (see **RC9**), the peak value of the correlation curves is dependent on the relation of the reconstructed wind speed at wind turbine B (U_B) and the advection speed of fluctuations between wind turbine A and B. If the wind speed at wind turbine B is overestimated the peak is found at $\tau_{norm} > 1$. The curves in Fig. 4, with peaks at $\tau_{norm} = 1.1$ and $\tau_{norm} = 1.2$ indicate that U_B is as expected overestimating the advection speed of wind speed fluctuations. Note that $\tau_{norm,intv}$ is used for the stretching and shrinking whereas τ_{norm} is only used to bin the stretchted or shrunk curves. We added for clarification:

p. 7, ll. 187f: Note that $\tau_{norm,intv}$ is only used for stretching and shrinking of the correlation curves and that τ_{norm} is used only for binning of the stretched or shrunk correlations.

RC11 *Figure 2 (and other places): a total of over 9 million intervals is mentioned. Are these statistically independent, or not? Please clarify.*

AC The analysed 600 s intervals are not statistically independent as they overlap by 599 s in the extreme case. Also, thinking of bigger gusts evolving through the wind farm, it is most likely that wind turbine pairs experience similar correlation states when being affected by the gust. To clarify the influence of the overlapping of the considered intervals we performed the calculations again using only non-overlapping intervals. The following figure (Fig. 1) shows a comparison of the results for non-overlapping and overlapping intervals exemplary for wind direction 270°. Figure 1a displays the comparison of the average correlation curves per wind farm row. Figure 1b displays the comparison of the average correlation curves per cluster. In general, the results of the non-overlapping intervals are similar to the results of the overlapping intervals and differ at most by about 10%. However, the comparison in Fig. 1a shows that this data set is at the limit of representing the correlations as the average correlation curves start to wiggle for $\tau_{norm} > 2$ due to the low number of data points. In total, only 8121 non-overlapping 600 s intervals are available for 270°. For all wind turbine pairs, 11514 intervals are available as multiple winter turbine pairs are available in the same interval. The 8121 intervals resemble a measurement time of 56 days.



(a) Average power output fluctuation correlation per wind farm row.

(b) Average power output fluctuation correlation per cluster.

Figure 1. Comparison of the average power output fluctuation correlation for wind direction interval 270° of non-overlapping and overlapping intervals. For both plots, the average correlation curves for non-overlapping intervals are marked with 'NO' and plotted with a dashed line. The average correlation curves for overlapping intervals are plotted in both cases as solid line.

RC12 *Figure 4: Why are the results not symmetric? I.e. for example 260 shows pronounced peak, but 280 degree does not. This aspect should be discussed. See also my above question on the selection of the 90 and 270 degrees wind directions.*

AC Indeed, this effect could be caused by the asymmetric layout of the wind farm as the wind turbines are not fully horizontally aligned. Also, Fig. 4 includes all wind turbines within the wind farm. As the lower part of the wind farm shows a triangular shape while the upper part is nearly vertical, this difference in the layout could also influence the correlation curves. A more detailed study of this phenomena is not planned in this analysis. We added the following text regarding Fig. 4:

p. 9, ll. 231f: In contrast to 90°, the correlations for 270° are more defined and show slightly larger peak values. This may be due to the asymmetric wind farm layout (cf. Fig. 1). The deviation between the average correlation curves for wind directions around 260° and 280° could be as well caused by the not entirely horizontally aligned wind turbines and by the triangular shape at the lower part of the wind farm, however, this phenomena is not further investigated in this analysis.

RC13 *Line 203: For wind directions approaching 0° and 180° the wind turbines in a pair are oriented more perpendicular to the wind. Fluctuations reach the downstream turbine earlier. ==> If the turbines are perpendicular for these wind directions, what is then the "downstream" turbine?*

AC Considering an exemplary wind turbine pair where one wind turbine is labelled as wind turbine 1 and the other as wind turbine 2: we chose to set wind turbine 1 in a pair as upstream wind turbine for the 10° wind direction intervals from 0° to 170° and wind turbine 2 as upstream for wind direction intervals from 180° to 350°. As the peak of the correlations curves for wind directions around 0° and 180° is expected to be located around $\tau_{norm} = 0$, definition of upstream and downstream wind turbine does not affect the results here. This means for 90°, wind turbine 1 is be the upstream wind turbine (A) and for 270°, wind turbine 1 is the downstream wind turbine (B) and vice versa for wind turbine 2.
We added the following text:

p. 8, ll. 204f: For 10°-wind direction steps from 0° to 170° we treat the pairs according to Tab. A with reversed order and for the 10°-wind steps from 180° to 350° we treat the pairs with the given order. This means even for wind directions where both wind turbines of a pair are parallel to the wind direction, the 'upstream' wind turbine A is chosen according to the table.

And we revised:

p. 9, ll. 224f: For wind directions approaching 0° and 180° the wind turbines in a pair are oriented more perpendicular to the wind direction and fluctuations reach both wind turbines A and B at nearly the same time.

RC14 *Line 224: Normalized by what?*

AC Normalised by the average power output of the upstream wind turbine A. Added in the text as follows:

p. 10, ll. 241f: Further, the power difference (normalised by the average power output of the upstream wind turbine A) and the average standard deviation of the power output fluctuations of both wind turbines in a pair are determined to analyse the flow conditions.

RC15 *Table 2 and other tables: If possible, I believe it would also be useful to mention the average power outputs of the wind turbines A and B*

AC We agree this would be a valuable information. Unfortunately, absolute values power values of wind turbines are problematic in terms of confidentiality we chose to only stick to the statistics we also used for the clustering of the correlation states.

RC16 *Line 250: "Even though such wind turbines are filtered out for the analysis, they still influence the surrounding wind turbines in an unpredictable way." ==> Please clarify the meaning of this statement. If the data is filtered such that all turbines are operations what effects are then not filtered for?*

AC This means that intervals where wind turbines are derated or turned off are not considered for the calculation of the correlation of power output fluctuations. However, a wind turbine that is turned off or derated influences the flow within the wind farm and thus, the surrounding wind turbine pairs and their correlation. As example, a wind turbine could be turned off for certain time interval. This means this wind turbine is not considered for the calculation of correlations for that interval. However, a downstream wind turbine could be operating normally and be considered during that time interval. The inflow of the downstream wind turbine is affected by a higher wind speed as the flow can recover due to the turned-off upstream wind turbine. This would result in a different correlation state for the regarded wind turbine and its downstream wind turbine in comparison to other pairs in the same rows due to the affected inflow. We revised the text as follows:

> p. 13, ll. 277f: For example, if a wind turbine is turned off for a certain time interval, it is not considered in the analysis, but it still influences the flow conditions within the wind farm and the statistics or correlations of surrounding wind turbine pairs. Thus, a considered wind turbine pair downstream of the non-operating wind turbine could show a different correlation than if the upstream wind turbine would be turned on.

RC17 *Figure 7 (line 260-263): If figure 7 is just showing two lines already shown in figure 4why do we need this additional figure?*

AC Thank you for the notice, we removed Fig. 7.

RC18 *Line 264-265: "into a reasonable set of groups and a greater number of cluster did not lead to further clusters of importance for the present analysis (see appendix B)." ==>Please clarify this statement. Also after reading the appendix this was not quite clear to me. What does "reasonable" mean? And what is a cluster of importance?*

AC When grouping the data into 6 instead of 5 clusters, only clusters with similar correlation curves are found which show a slight deviation in the standard deviation of the wind turbines in a pair. For the added cluster the standard deviation of the power output fluctuations is greater for the upstream wind turbine A instead of the downstream wind turbine B. We revised the text and the appendix as follows:

> p. 13, ll. 297f: k is set to five clusters. This number was empirically chosen as the data was grouped into a reasonable set of groups with clearly distinguishable correlation curves (correlation states). A greater number of clusters lead to further clusters with similar correlation curves. The only difference found was in the standard deviation of the power output fluctuations of the wind turbine pairs. Here, the cluster indicate a higher standard deviation for the upstream wind turbine A instead of the downstream wind turbine B. This slightly abnormal behaviour is shown in more detail in appendix B.

> p. 19, ll. 389f: As mentioned in Sect. 4, the number of clusters chosen for the present analysis was $k = 5$. This decision was made based on the results for $k = 6$ presented in Figure B1 and Fig. B2. For wind direction 90°, six clearly separable correlation curves are found. Comparing Fig. B1 to Fig. 7, it shows that Cluster 2 of Fig. 7 seems to be separated into to clusters (Cluster 2 and 3 of Fig. B1).
> For wind direction 270° only 5 clearly separable correlation curves are found whereas one is overlapped by a very similar one. Comparing Fig. B2 to Fig. 8, it shows that Cluster 3 of Fig. 8 seems to be separated into two similar clusters (Cluster 3 and 4 of Fig. B2). The new clusters also do not reveal any further characteristics.
> Looking at the statistics of the correlation curves listed in Tab. B1 it further can be found that for wind direction 90° Cluster 2 shows a higher standard deviation for wind turbine A instead of B while Cluster 3 shows a higher standard deviation for wind turbine B instead of A similar to all other Clusters. For wind direction 270° Cluster 4 shows a higher standard deviation for wind turbine A instead of B while Cluster 3 shows a higher standard deviation for wind turbine B instead of A similar to all other Clusters.
> The correlation curves and statistics imply that a further separation of the statistics with $k > 5$ does not reveal any correlation states which are more significant than the ones found for $k = 5$. However, clustering with $k > 5$

might result in a further distinction of flow states for wind turbine pairs based on the standard deviations of wind turbines A and B but are not further investigated as this effect is not included in the scope of the work presented here.

RC19 *Line 308: Please be specific so the conclusion section can be read independently.*

AC Thank you for noting this, the conclusion was fully revised. Please refer to the provided LaTeXDiff file.

RC20 *Line 320: It is unclear to me what can be learned from these different clustering approaches. Why are these specific ones suggested?*

AC The benefits of these algorithms have been clarified as follows:

p. 17, ll. 376f: Also, it is worth considering alternative clustering methods like k-medoids (Kaufman and Rousseeuw, 2008) which is less sensitive to outliers compared to k-means or Density-Based Spatial Clustering of Applications with Noise (DBSCAN) (Ester et al., 1996) which is also less sensitive to outliers and has no fixed cluster shapes and no predefined number of clusters like k-means.

Authors response to comments from referee #2 - Mark Kelly

General comments

RC1 *The analysis of power output correlations across a wind farm can certainly be relevant within wind energy. This is certainly a challenging task given the data analyzed and its limitations; the latter has been only partly addressed. The abstract does not appear to include motivation for the study, and the introduction also lacks clear motivation and/or justification; why/how is this work relevant?*

AC Thank you for pointing this out. We present an approach to analyse space-time correlations of the power output fluctuations of wind turbine pairs operating in a free-field wind farm. The analysis considers the effect of varying flow conditions within the wind farm and uses exclusively high-resolution SCADA data of the wind turbines. To account for these varying flow conditions, we propose a set of parameters to describe the correlations based on an approach to sort the data into groups. The space-time correlation of wind turbine pairs is for example of importance for wind turbine control and short-term load or power forecasting where the measurements from the upstream wind turbine are used to predict the wind speeds or load affecting the downstream wind turbine. We revised the abstract and conclusion carefully as well as the discussion of the results. Please see the revised manuscript with the highlighted changes.

RC2 *Unfortunately there are a number of issues with the submitted draft, such that it requires at least major revisions. A number of plots showing pair-wise power output correlation versus normalized lag are shown; but their statistical significance is not evident, nor argued thoroughly, nor put within any context of the scales of atmospheric inflow fluctuations. (One can see by the repeated trends, of course, that the plotted R(τ_{norm}) are not simply noise, despite being at most ∼0.1–0.4 depending on the data selection.)*

AC We agree that further that the statistical significance of the results needs further clarification. The results presented here show correlation coefficients of about 0.16 or 0.21 at first appear rather low. However, comparing these results to the findings of Lukassen et al. (2018) in the LES and of Bossuyt et al. (2017b) in the wind tunnel, it shows that our results are reasonable. The wind turbine distances, and wind speeds considered in the LES are similar to our data. The peak of the space-time correlation of the wind speed at two streamwise aligned wind turbine positions was found at about 0.5. In the wind tunnel experiments the peak of the space-time correlation of the reconstructed power output of a wind turbine in the first and second row was found at about 0.55 for aligned wind turbines and at 0.2 if the wind turbines are staggered. Here, the spacing of the wind turbines was also similar to ours and the thrust coefficients of the discs resemble operation below rated wind speed. Thus, considering the varying flow conditions in our data set, the peaks of about 0.16 or 0.21 are rather good in comparison to the results in the steady flow conditions.
We clarified the relevance of the presented correlations as follows:

> p. 8, ll. 218f: The maximum correlation around 0.2 may seem rather low but is reasonable considering the high variability in the flow and wind turbine dynamics in free field measurements. As comparison, in the LES study of Lukassen et al. (2018), a maximum correlation coefficient of about 0.5 was found for space-time correlations of wind speeds measured at comparable distances with comparable wind speed. In the wind tunnel experiments by Bossuyt et al. (2017b), a maximum correlation of about 0.55 was found for the space-time correlation of the reconstructed power output of discs placed at comparable distances with comparable wind speeds.

p. 17, ll. 357f: For 90° the peak of the correlation increased via clustering from 0.16 to 0.32 and for 270° the peak of the correlation increased from 0.21 to 0.41. A value of 0.41 is close to the correlations found in the LES study by Lukassen et al. (2018) and experiments by Bossuyt et al. (2017b) which were between 0.5 and 0.55 for similar wind turbine spacing and similar wind speeds.

RC3 *The methods used are not explained in sufficient detail, with references to such also lacking. As currently reported, the study would not be reproducible by a reader. The results need to be more clearly presented, and also interpreted, by the authors—in addition to the inclusion of relevant details, motivation, and significance of the study.*

AC We agree and clarified the methods, especially in Sect. 2.2. Further we clarified the description and discussion of the results. Please see the revised manuscript with the highlighted changes.

RC4 *There are errors in language throughout; I have included some correction examples in the last section below, but suggest that the next version be proofread by somebody with near-native level fluency.*

AC Thank you for pointing this out. We proofread the paper and corrected the linguistic errors. Please see the revised manuscript with the highlighted changes.

<u>General comments</u>

RC5 *l.8: what is meant by 'correlation states'? Lines 7–9, starting with 'Most importantly', should be reworded. To be more direct: you are using a clustering algorithm (k-means clustering) to group similarly correlated turbine pairs, in order to examine the spatial variation of correlations between turbines and determine the key parameters affecting such correlations.*

AC Correlation states are correlations caused by varying flow conditions which are found for certain wind turbine pairs within the wind farm based on the introduced parameters: standard deviations of the power output fluctuations and the power difference of wind turbine in a pair. The abstract was revised as follows:

p. 1, ll. 1f: Space-time correlations of wind turbine pairs provide information on the flow conditions within a wind farm and on the interactions of the wind turbines. Such information plays an important role for the control of wind turbines and short-term load or power forecasting. However, the challenge to analyse space-time correlations of power output fluctuations of wind turbine pairs in a free field wind farm are the highly varying flow conditions. Here, we present an approach to investigate space-time correlations of power output fluctuations of wind turbine pairs in free field based on high-resolution SCADA data, which overcomes the challenge of highly variable flow conditions within the wind farm. Using eight months measurements from an offshore wind farm with 80 wind turbines, the influences of different parameters on the correlation of power output fluctuations are analysed. Wind direction investigations show that correlations of power output fluctuations of wind turbine pairs are highest for streamwise aligned pairs and decrease towards spanwise pairs. Further, it is found that the correlation of power output fluctuations of streamwise aligned wind turbine pairs depends on the location of the wind turbines within the wind farm as well as the inflow conditions (free-stream or wake). The main outcome is that the correlation of streamwise aligned wind turbine pairs can be characterised by the standard deviations of the power output fluctuations and the power difference of the wind turbines in a pair. Evaluating these parameters with the data-driven clustering algorithm *k*-means, wind turbine pairs with similar power output fluctuation correlations are grouped depending on these parameters and independent from their location. These groups are here referred to as correlation states. With this approach we account for the highly variable flow conditions inside a wind farm

> which influence the correlations in an unpredictable way. As a final result we shows that these parameters lead to clearly distinguishable correlation states.

RC6 *l.9–10: The phrase 'next to' isn't appropriate here; it seems you're wanting to say 'in addition to' or similar. Also, do you mean the location of a turbine pair is most important, or the relative locations/distance?*

AC The location of a wind turbine pair within the wind farm is most important. Please find the revised abstract in **RC5**.

RC7 *l.38: in terms of correlations, the wind farm was not "infinitely large", was it? I.e., were there not periodic boundary conditions used in the LES?*

AC Yes, periodic boundary conditions were used. The text was revised for clarification as follows:

> p. 2, ll. 44f: In an LES study by Lukassen et al. (2018) velocity space-time correlations within a wind farm with periodic boundary conditions (modelling a periodic array of wind turbines) were analysed and modelled analytically.

RC8 *l.40: by 'variance of the wind velocity', do you not mean strength of turbulence in the prescribed inflow?*

AC If you refer to the turbulence intensity: both parameters, the variance of the wind velocity and the mean wind velocity in the inflow enter the model as explicit parameter and not as the combined parameter turbulence intensity. To clarify this, the text was revised as follows:

> p. 2, ll. 45f: The velocity fluctuations, which are directly related to power output fluctuations showed pronounced space-time correlations. Furthermore, the variance of the wind velocity and the mean velocity turned out to be important parameters in the modelling set up.

RC9 *l.55,l.64 and elsewhere: you haven't (yet) defined "correlation state"*

AC Thank your indicating this. We define correlation states the average correlations found by the clustering of the statistical parameters: the standard deviations of the power output fluctuations and the power difference of wind turbine in a pair. The definition of correlation states was added as follows (also see **RC5**):

> p. 2, ll. 60f: In this paper we investigate the influencing factors on the correlation of power output fluctuations of wind turbine pairs and introduce parameters to distinguish different correlation curves, here called correlation states. These parameters are then evaluated with a data-driven clustering algorithm with the aim to group the data according to the underlying correlation states.

RC10 *l.71: why "non-axisymmetric"? Do you mean asymmetric?*

AC Yes, thank you. We corrected the sentence as follows:

> p. 3, ll. 78f: They are installed in a grid like, slightly asymmetric pattern with a triangular shape towards south (see Fig. 1).

RC11 *l.74-76 and afterward: How did you calculate the wind direction and U? What transfer function(s) were used, and how was this blended with speed implied by measured power?*

AC Unfortunately, U is provided as a variable within the data set. It is not measured but directly related to the measured power and reconstructed from the wind turbine (controller) settings. Details on the reconstruction are not available. Depending on U, the correlation curves stretch or shrink (see p.6, eq. 3). Thus, if the recalculated wind speed differs from the actual wind speed, the normalised correlation curve might be slightly shifted to a larger τ_{norm}. However, U affects the normalisation of the correlation curves in a consistent manner for all wind turbines. For this reason, we consider U as reasonable variable in the context of this analysis. We revised the description of U and how it affects the analysis:

> p. 3, ll. 81f: The processed signals include the generated power P, the azimuth angle of the wind turbines (i.e. the nacelle direction) θ, the nacelle based wind direction φ (measured relative to θ), the pitch angle β of each blade, and a reconstructed wind speed U.
> The reconstructed wind speed U is not directly measured but provided as a variable which results from the measured power and control variables of the wind turbine. Due to that, U is considered as an approximated and idealised value which does not include wind speed independent power reduction, e.g. by misalignment of the wind turbine due to measurement errors of the wind direction. In the context of this work, it can still be used for assessing the effect of the wind speed on the correlations of power output fluctuations of wind turbine pairs which is further discussed in Sect. 2.2.

> p. 7, ll. 179f: As mentioned before, U_B is reconstructed and might differ from the actual wind speed affecting the wind turbines. However, in the context of this normalisation the effect on the resulting correlations curves is marginal as the correlation curves may only be slightly shifted due to the deviation to the real wind speed.

RC12 *l.77: do you mean that the yaw error was not used in the nacelle wind speed transfer function/correction?*

AC The yaw measured by the wind vane could be taken into account for the reconstruction of the wind speed. However, a wind turbine could have a further unknown yaw misalignment which does not show in the data as it is caused by false measurements, inaccurate or false sensor calibrations or false sensor installation. In this case the wind turbine would have a greater yaw than the measured one and it would measure less wind speed due to that. As mentioned in **RC11**, unfortunately, we have no further information on the reconstruction.

RC13 *l.87–89: did you consider the across-farm variation in wind direction, with suitable averages of upwind turbines?*

AC No, we did not consider the across-farm variation in wind direction. The mentioned inaccuracies in the θ_i and φ_i measurements (l. 92-98) prevent a precise evaluation of different wind directions within the wind farm, i.e. the wind directions at certain wind turbines. Thus, we average the wind direction over all available wind turbines within the wind farm considering the effect of certain wind turbines facing another direction. Please see the description of the azimuth angle θ and the description of the average wind direction φ_{av}:

> p. 3, ll. 89f: The azimuth angle θ of the wind turbine refers to the direction it is facing in its preset reference system. This system does not necessarily exactly match to the global geographical one due to the measurement inaccuracies of the azimuth angle and a potentially inaccurate north orientation of the reference system of each wind turbine (cf. Bromm et al., 2018).
> The nacelle based wind direction φ is estimated based on the measurements of two 2D sonic anemometers installed behind the rotor of each wind turbine. These measurements have to be treated with care as the measured flow behind the rotor is disturbed by the rotation of the rotor and the nacelle itself. Thus, it is only an estimation of the wind direction and yaw of the wind turbine. However, as shown by Dai et al. (2017), wind direction fluctu-

ations at reasonable yaw angles ($< 45°$) have only little effect on the power output fluctuations of wind turbines and thus inaccuracies in φ have no major influence on the performed analysis. The combined measurements of θ_i and φ_i define the wind direction Φ_i at the i-th wind turbine.

p. 4, ll. 98f: For assessing an average wind direction for the wind farm, we average over Φ_i of all wind turbines to reduce the influence of false measurements of single wind turbines. Due to the size of the considered wind farm, the wind direction is not expected to be consistent throughout the whole wind farm. Single wind turbines could be facing different wind directions compared to the average wind direction of the wind farm (cf. Schneemann et al., 2020; Sanchez Gomez and Lundquist, 2020). The wind direction of the wind farm averaged over all available wind turbines is defined as Φ_{av}.

RC14 *l.111 and Table 1: how did you determine the pitch threshold?*

AC This value was empirically chosen based on the analysed data set. In this case, this was the threshold for non-pitched blades. For clarification we added the following text:

p. 5, ll. 122f: Hence, to fully exclude pitching wind turbines, the data is filtered for any pitching activity. Please note that for this specific data set this implies that $\beta < -1.3°$.

RC15 *l.112–116 and Table 1: what is the yaw misalignment threshold? What about φ change per 600s?*

AC There is no threshold for yaw misalignment within the 600 s intervals that means no yawing at all. The maximum possible misalignment is thus defined by the controller settings of the wind turbines which define at what yaw misalignment the wind turbine starts yawing. As the wind vane measurements are highly dynamic within the considered 600 s intervals a limitation of φ would lead to a significant loss in the amount of considerable correlation intervals as nearly no intervals with consecutively measured values would be available after filtering.

RC16 *l.120–121: why not report the variation of angles, instead of only the mean with 10-degree tolerance?*

AC Within the scope of this work we introduce an approach to analyse correlations of power output fluctuations of wind turbine pairs which copes with the varying flow conditions within the wind farm. An investigation of the influence of the misalignment of individual wind turbines from the average wind direction of the wind farm is not part of this analysis and thus not further taken into account.
Also, Dai et al. (2017) presented that wind direction fluctuations of wind turbines have only a small influence on the power output fluctuations of (yawed and aligned) wind turbines. Please see the text including description of the azimuth angle θ in **RC11**.

RC17 *l.155–159: mention the use of Taylor's hypothesis here—and the assumption you're thus using over the entire range of τ_{norm}. There are several references you should check (and cite) regarding this.*

AC Thank you for your notice. Indeed, our approach is similar to Taylor's hypothesis. However, we do not further investigate it in this context. We revised the text as follows:

p. 6, ll. 166f: Similar to Taylor's hypothesis (Taylor, 1938) we assume that depending on the wind speed, wind structures responsible for power output fluctuations measured at an upstream wind turbine A, take some time to travel the distance to the downstream wind turbine B.

RC18 *l.163–166: Your statement about $\tau_{norm} > 1$ has an implication: if you used the average speed between turbines A and B (instead of U_B), then wouldn't $\tau_{norm} = 1$, unless the propagation speed is somehow otherwise affected? It's difficult to defend using just U_B*

AC Yes, this is correct. We stick to U_B as reference, since the average advection speed between the wind turbines is not available. The only available measurements are the wind speeds at the upstream wind turbine A and the downstream wind turbine B. As the upstream wind turbine mostly affected by higher wind speeds than the downstream wind turbine B, we choose U_B as reference. Of course, U_B is also an overestimation of the actual average speed between wind turbine A and B. However, U_B shrinks or stretches the correlation curves and an overestimation slightly shifts the normalised correlation curves towards larger τ_{norm}. This effect is consistent on all wind turbines and thus we consider the usage of U_B as reasonable. We revised Sect. 2.2 to clarify this dependency:

p. 3, ll. 81f: The processed signals include the generated power P, the azimuth angle of the wind turbines (i.e. the nacelle direction) θ, the nacelle based wind direction φ (measured relative to θ), the pitch angle β of each blade, and a reconstructed wind speed U.
The reconstructed wind speed U is not directly measured but provided as a variable which results from the measured power and control variables of the wind turbine. Due to that, U is considered as an approximated and idealised value which does not include wind speed independent power reduction, e.g. by misalignment of the wind turbine due to measurement errors of the wind direction. In the context of this work, it can still be used for assessing the effect of the wind speed on the correlations of power output fluctuations of wind turbine pairs which is further discussed in Sect. 2.2.

p. 7, ll. 175f: Due to this definition of $\tau_{norm,intv}$ and τ_{norm} (see Eq. **??**), the peak of the correlation curves is expected to be found at $\tau_{norm} = 1$ if the advection speed of the wind speed fluctuations matches the wind speed affecting B. Thus, in partial load situations where wind turbine B is in the wake of wind turbine A, the peak is expected to be at $\tau_{norm} > 1$. Here, the reduced wind speed in the wake recovers slowly, so that the wind speed affecting wind turbine B, i.e., U_B is already partly recovered and hence larger than the advection speed of the fluctuations. As mentioned before, U_B is reconstructed and might differ from the actual wind speed affecting the wind turbines. However, in the context of this normalisation the effect on the resulting correlations curves is marginal as the correlation curves may only be slightly shifted due to the deviation to the real wind speed.
In a next step, the correlation curves with the normalised lag $\tau_{norm,intv}$ are discretised using a histogram with a reference time lag of

$$\tau_{norm} = \tau \cdot \frac{U_{max}}{x_{AB,mean}} \tag{4}$$

where τ is the time lag (0 s to 300 s), U_{max} is an artificially introduced velocity which has to be at least equal to the maximum possible wind speed to fit all normalised curves (here $U_{max} = 13\,\mathrm{ms}^{-1}$). $x_{AB,mean}$ is the average distance between wind turbine A and wind turbine B of the considered wind turbine pairs. Note that $\tau_{norm,intv}$ is only used for stretching and shrinking of the correlation curves and that τ_{norm} is used only for binning of the stretched or shrunk correlations.

RC19 *l.181: why 20deg interval? How does this compare to the variation of φ across all turbines for a 10-minute periods? The latter is likely important to describe the inflow state and variability of the wind field (not to mention yaw error).*

AC We investigate the average correlation of all wind turbine pairs in the wind farm for different main wind directions. These main wind directions are the wind directions averaged over the whole wind farm. The 20° interval is the result of the 10-degree tolerance in the wind direction measurements of the wind turbines. In Fig. 3 we present the average correlation of all wind turbine pairs in the wind farm for the corresponding average wind farm direction. As mentioned before, in the scope of this work we do not investigate the influence of wind direction fluctuations or the influence of wind turbine misalignments on the correlation of wind turbine pairs.

RC20 *p.8/l.201–203: Indeed* $\rho = 0.2$ *is not generally considered to be statistically significant. Have you tried windows of different lengths (other than 300s)? Have you considered the integral timescale of the incoming turbulence? What about the wake turbulence?*

AC Yes, a correlation coefficient of 0.2 is generally not considered to be statistically significant, however considering the effect of the high dynamics in the flow of free-field measurements it is reasonable. Especially when comparing these findings to the LES simulations of Lukassen et al. (2018) where wind speed space-time correlations at one wind turbine distance showed a correlation coefficient of 0.5. In the wind tunnel experiments of Bossuyt et al. (2017b) a correlation of about 0.55 was found for the space-time correlation of wind turbines with one wind turbine distance. This comparison is also clarified in the paper:

> p. 8, ll. 218f: The maximum correlation around 0.2 may seem rather low but is reasonable considering the high variability in the flow and wind turbine dynamics in free field measurements. As comparison, in the LES study of Lukassen et al. (2018), a maximum correlation coefficient of about 0.5 was found for space-time correlations of wind speeds measured at comparable distances with comparable wind speed. In the wind tunnel experiments by Bossuyt et al. (2017b), a maximum correlation of about 0.55 was found for the space-time correlation of the reconstructed power output of discs placed at comparable distances with comparable wind speeds.

The integral timescale was not investigated, but it can be stated that the temporal autocorrelation of a wind turbine decorrelates in the considered time intervals of 300 s.
Further, the wake turbulence has not been taken into account in detail. However, it is resembled in the standard deviations of the power output fluctuations which are introduced as parameter. The cluster results clearly show the influence of the standard deviation on the correlations of wind turbine pairs. The highest correlation is found for the cluster with the highest standard deviations.

RC21 *Table 3: is it reasonable to include 3 significant digits in the correlations listed? (or 5 in the power?) Such second-order statistics do not converge so easily within 10 minutes...*

AC Thank you for pointing this out. We adjusted Tab. 2 to 4 and B1.

RC22 *l.253–255: While this reviewer has some familiarity with k-means clustering, how is a reader supposed to be able to understand (let alone repeat) the analysis reported here? Please include appropriate references and details.*

AC We agree that further information is necessary, thus a short description of the *k*-means algorithm was added:

> p. 13, ll. 284f: *k*-means is an algorithm which iteratively sorts data into *k* clusters. After choosing an initial centre for each cluster (centroids) within the data, all data points are assigned to their nearest centroid. Afterwards, the new centres of the clusters are calculated based on the assigned data points. These steps are repeated until a previously defined number of iterations is reached or the centres of the clusters no longer change. Finally, the data is distributed into *k* clusters. The result of *k*-means is dependent on the starting positions of the cluster centres. Thus, the algorithm can be repeated with changing starting points for the clusters to find the best possible solution.

The details of the performed clustering are given here:

> p. 13, ll. 293f: The clustering is performed using the *k*-means algorithm of MATLAB (MATLAB, 2019) based on Lloyd (1982), using random sample points as initial centroids to find the best solution. To avoid the generation

> of local centroids the clustering is repeated ten times and the run with the clusters with the lowest sum of point-to-centroid distances within the clusters is chosen. As a distance metric for the clusters, the squared Euclidean distance chosen. The maximum number of iterations is set to 300.

RC23 *l.293 and elsewhere: instead of just 'filtering', perhaps you should use a term like 'data selection process'; recall that in the spectral sense a filter means something else, and such filtering could be expected for the kind of analysis you do here.*

AC We agree that 'filtering' could refer to something else dependent on the context. The term 'data filtering' or 'filtering of data' is commonly used and known in data science. Based on this we came to choose the term 'filtering' in this context.

RC24 *l.296: "Deviations from the 90° and 270° wind directions result in a decreased correlation" is out of context here; this and the statement after it do not make sense as written.*

AC We agree, this issue is resolved in the revised conclusion.

RC25 *l.299–300: pairs within the first (upwind) row of turbines have little correlation not simply because of the 'free-stream' inflow, but because their spacing is greater than the transverse integral length scale of the turbulence.*

AC With pairs within the first row we were referring to streamwise aligned pairs where the upstream wind turbine A is located in the very first row and the downstream wind turbine B is located in the second row of the wind farm. To clarify this, we added and revised the sentence:

> p. 16, ll. 344f: Wind turbine pairs, where upstream wind turbine A is located in the first row and downstream wind turbine B is in the second row of the wind farm, show no correlation with large normalised power differences and small standard deviations of power output fluctuations. This is most likely caused by the free-stream inflow of the upstream wind turbines A of the pairs.

RC26 **RC23:** *l.308–309: simply using 'previously defined' or 'chosen statistics' is somewhat obfuscatory and not really appropriate in a conclusion/summary; it does not explain to the reader which 'statistics' you are considering.*

AC We absolutely agree with this and resolve this issue in the revised conclusion.

RC27 *l.309–311: why not just use joint distributions, and conditional statistics? How is kmeans more helpful?*

AC Considering the three introduced parameters, the evaluation of joint distributions is more complex as more intermediate steps are needed. In addition, the data has to be grouped manually to average the correlation curves. K-means on the other hand performs everything in one run and is easily adaptable to further parameters.

RC28 *l.311–312: this statement is not understandable without more context; please help the reader, and interpret it also.*

AC We agree, this issue is resolved in the revised conclusion:

> p. 17, ll. 353f: The clustering showed similar results for wind directions 90° and 270° and the clusters showed clearly distinguishable parameters which were directly related to the average correlation curve per cluster. Increased standard deviations combined with small power differences showed the most defined correlations with the highest peak. This combination was found for wind turbine pairs with a position more downstream in the wind farm but also including some wind turbine pairs from rows towards the front. For 90° the peak of the correlation increased via clustering from 0.16 to 0.32 and for 270° the peak of the correlation increased from 0.21 to 0.41. A value of 0.41 is close to the correlations found in the LES study by Lukassen et al. (2018) and experiments

by Bossuyt et al. (2017b) which were between 0.5 and 0.55 for similar wind turbine spacing and similar wind speeds.

RC29 *l.320–323: why were no details about this given in section 4?*

AC This is discussed in the revised appendix and the following text was added:

p. 13, ll. 297f: *k* is set to five clusters. This number was empirically chosen as the data was grouped into a reasonable set of groups with clearly distinguishable correlation curves (correlation states). A greater number of clusters lead to further clusters with similar correlation curves. The only difference found was in the standard deviation of the power output fluctuations of the wind turbine pairs. Here, the cluster indicate a higher standard deviation for the upstream wind turbine A instead of the downstream wind turbine B. This slightly abnormal behaviour is shown in more detail in appendix B.

Technical corrections

RC30 *l.6: 'correlation is' should be 'power correlations are'; 'towards' is not appropriate*

AC Revised.

RC31 *l.15: second 'and' should be 'while' or similar.*

AC Corrected.

RC32 *l.23: 'the respective' should be 'a respective'*

AC Corrected.

RC33 *l.27–29: need to re-word run-on sentence, including e.g. appropriate commas*

AC Corrected.

RC34 *l.33: remove 'a' before 'high'*

AC Corrected.

RC35 *l.46: 'of' should be 'between'*

AC Corrected.

RC36 *l.81: reference missing year*

AC Corrected.

RC37 *l.400: incorrect journal and doi for Valldecabres reference*

AC Corrected.

RC38 *l.403–404: the WindEurope reports appear to be missing some identifying information (e.g. doi, report number, etc.).*

AC Revised.

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