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Reply on RC2

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Author comment on "Non-stationarity in correlation matrices for wind turbine SCADA-data and possible implications for failure detection" by Henrik M. Bette et al., Wind Energ. Sci. Discuss., https://doi.org/10.5194/wes-2021-107-AC2, 2022

We thank the referee for his/her detailed comments. We are sure they helped increase the quality of our manuscript. In general, the proposed methodology in itself can be used to identify operational states without prior knowledge of the control system. It is true that the benefit for failure detection is not proven in the current paper, but only implied. We show that the different correlation structures can be detected automatically by clustering. This means that they are quite distinct and different. We are convinced that this implies benefits for failure detection by separating the space of what is normal into three smaller subspaces, from which deviations could be detected, especially if the method used to analyze failure directly depends on the correlation structure. A test and study of this benefit will be part of future research. We aim with this paper to encourage others to do this as well. We think that it is a good idea to more clearly state this in the text of the paper and change "implications" to "possible implications" in the title.
We also extended the paragraph discussing implied benefits for failure detection in the introduction. We included citations from Tveten (2019) showing the strong influence of changes in correlation on PCA and Zimroz et al. (2014) showing that accounting for non-stationary operating conditions improves failure detection results.

We are especially grateful for the specific comments, which we will address separately in the same order they were made by the referee.

- As correctly pointed out, the pitch angle is an interesting control variable. In our data set, however, it contains many missing values. This reduces the number of usable epochs from 749 to 171. As the turbine type looked at in this study aims to either keep rotation and/or power constant, it is not necessary to look at the pitch angle to distinguish these regimes. Be that as it may, we understand that the pitch angle is a very prominent variable when looking at wind turbines and this point rightfully brought up by the referee could irritate many readers. We have therefore decided to apply a method to fill the missing values in the pitch angle time series and include the basic clustering analysis with pitch angle in the manuscript as well. This can be found in a newly added section 4.2.
  The use of directly coupled observables is thought to be beneficial for understanding the entire correlation structure. As in many complex systems groups of correlated

observables occur. Our analysis shows that the states found are different in the inter-correlation between groups not in the intra-correlations inside the groups. Further studies could investigate a minimal set of observables needed for this distinction (starting from our observables and removing groups the set of "Active Power", "Rotor RPM" and "Wind Speed" could be considered.) as well as larger sets of observables. Of course, this could also change the number of clusters, which need to be considered. When using the proposed method as a pre-processing for failure detection, it will have to be fitted on the observables needed for that specific failure detection method.

- The two observables do not decouple from each other, but rather "from the others". This means that these two stay closely correlated as is mechanically reasonable, but are no longer correlated to the other observables. We refined this wording in the revised manuscript.
- We still think that finite control time may in some cases play a role, but we agree that the 30 minute window is the dominant cause here. We will emphasize this point in the revised manuscript.
- As pointed out in the answer to specific comment one, the use of pitch angles is problematic with our data. Some misclassified points are to be expected always when using stochastic clustering methods as can also be seen in the newly added section 4.2 where pitch angle is included in the analysis. In our data set we did not find a better set of observables to consider, however we share the referees hope that with larger data sets (time- and observable-wise) the method could be improved further in the future.
- The evolution of states over time is shown once to clearly show that – in contrast to some other complex systems such as finance – the dependence does not seem to be time and no states die out or emerge.
  While we agree with the the referee that scatter plots would be interesting for comparison, we cannot show them due to our cooperation agreement with the data provider. In response to the referees' comment we specifically asked, if we could show them in this case, but we are not allowed to. We have, however, included the explanation for the difference in values in the revised manuscript:
  The power curve (active power in dependency of wind speed) as given by the manufacturer is one line. Accordingly, there is exactly one value ˜vnom which marks the starting point for nominal power production. In reality, especially when looking at high-frequency data, there will always be an area around this line which is realized. The value ˜vnom lies in the middle of this smeared out power curve. At this wind speed nominal power output can be reached but is not yet constant. With even higher wind speeds, it becomes less and less likely that the actual power produced lies beneath the nominal value. Only when this probability nearly vanishes, a change in correlation structure is detectable by our method. It is therefore reasonable that our value vnom lies higher than ˜vnom. While our value is therefore well suited to distinguish correlation states, it cannot be directly compared with the nominal wind speed given by the manufacturer of a turbine. We have confirmed this by looking at scatter plots of our data but cannot show them in this paper due to data confidentiality.
  We thank the referee again for pointing out that it was missing.
- We are very grateful for this comment. The referee is certainly correct that a few sentences about this in the paper are in order. We will add them in the revised manuscript. The general idea is to classify based on wind speed as this was shown to be the dominant factor dividing the three states. The overlap between two states could be used to calculate a certainty of the analysis made. If one is looking to minimize false alarms for example, one could also apply any method to both states and then consider the one indicating less failure. Abnormal operating conditions like curtailment need to be considered and used as additional post-processing when applying this in practice. These things must be considered and tested when actually using our method as a pre-processing for any analysis. As we have said, we will add this in the revised manuscript.
- We agree that they are not "defined" by our method, but are, of course, introduced by the manufacturer. We will change this wording to "enables the distinction of multiple

operational states” to more clearly point out that we can find these states defined by the manufacturer without prior knowledge.

- We are unaware of publications that use automatic separation into operational/correlation states before the application of the actual failure analysis process. This also because high-frequency data is not always available. The distinction into operational states is only sensible if the interval that can be looked at is not larger than the usual time it takes for wind conditions to change. The improvement for “all techniques” is just conjecture, which led to the usage of the word “might”. We want to raise awareness of the non-stationarity in the correlation structure and the possibility to use this for pre-processing into separated normal states. We want to encourage researchers and analysts to try this out and will do so ourselves in future work. An example to underline our conjecture is a neural network: We do not really know what it does internally, but we do know that it needs to account as best it can for all mechanisms in the system. With our proposed pre-processing the neural network does not need to learn to distinguish different control regimes as this is already done. We conject that this could increase accuracy or reduce training time, or the size of the training data set needed.
  For methods directly dependent on the correlations such as PCA the implication is clearer: As the principal components are the eigenvectors of the correlation matrix, a changing correlation matrix will also change the principal components and thereby the results of an analysis depending on them. The referee is correct in that this for now is still only implication. Detailed analysis of the possible benefit will be part of future work.
  We thank the referee for recognizing that automated detection is interesting in any case.
- We have not proven or quantified the aid our method could provide for failure analysis in this paper and aim to do this in the future. No reference using the proposed methodology can be given yet as it is new. We hope to encourage researchers to consider this pre-processing in the future and analyze its benefit.
  We think that the word “implications” already describes this, in contrast to e.g. “consequences”, but agree that it needs to be pointed out more prominently. We will do so in the text of the manuscript where necessary and propose to change the title to “Non-stationarity in correlation matrices for wind turbine SCADA-data and possible implications for failure detection”.

We hope that our answers are satisfactory and want to thank the referee once more for many helpful suggestions.