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WIND ENERGY SCIENCE DISCUSSIONS

Interactive comment on "The Power Curve Working Group's Assessment of Wind Turbine Power Performance Prediction Methods" *by* Joseph C. Y. Lee et al.

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We thank the reviewer for conducting a deliberate review to improve our manuscript. In the following, the reviewer's comments are numbered, followed by our comments beginning with "Response:".

1. In general the authors use a high number of acronyms throughout the article, which may confuse the reader and should be avoided where possible.

Response: This manuscript describes a large data science and data sharing project, and we define many parameters in the manuscript to give the full context about this

multi-year effort for the readers, and thus the content is dense and is filled with acronyms. To address the reviewer's concern, we added the full phrases before using the acronyms for the first time, especially in the Figure captions (Figure 1, 5, 6, and 12), the Conclusions, and the Appendices. Table 3 also summarizes the abbreviations of the trial methods.

2. The definitions of "inner range" and "outer range" are clear, however the authors reference these definitions before a detailed explanation is provided. In addition, to give more context and add background to the work, clarification of how the "inner range" power curve compares to the manufacturer's power curve, which is commonly known at all levels in industry, should be provided.

Response: The current structure of the manuscript begins with an introduction of the challenges about the wind turbine power curve (Sect. 1.1), which involves the concept of the Inner Range and the Outer Range. Then we discuss the two definitions extensively as part of the methodology that the Power Curve Working Group specifically chose to use in the Share-3 exercise (Sect. 3.1). We understand that introducing the ideas in the Introduction without the details raises questions, hence immediately after the first mention of Inner Range and Outer Range in the Introduction, in line 34, we wrote "The definitions are discussed in detail in Sect. 3.1."

We also added the following from lines 217 to 220 to differentiate the Inner Range power curve and the reference power curve (often provided by the turbine manufacturers):

"Note that the Inner Range Power Curve is only valid for a subset of TI and wind shear conditions (Table 2), which resembles the premise of a typical reference power curve provided by turbine manufacturers. The Inner Range power curve is derived from the observed data, which differs from a reference power curve. We also do not use any reference power curves in this analysis because we do not require the participants of the Share-3 exercise to share them."

3. In section 3.1 the authors propose three definitions of “inner range”, without explaining why three definitions are given.

Response: Thank you for your comment. Lines 159 to 163 now read:

“We outline three Inner Range definitions in the Share-3 initiative because the PCWG analysis tool (Sect. 3.2) uses a specific definition to derive an Inner Range power curve for each data set. Depending on the data set, one of the three definitions is applied. For a data sample, the PCWG analysis tool first uses definition A as the default. If the resultant Inner Range data count under definition A is small (Power Curve Working Group, 2018), then the tool would switch to definition B. If the Inner Range data size is again small with definition B, then the tool would use definition C.”

4. In the conclusions, a more thorough discussion of how these methods can be improved in the future, to yield more statistically meaningful improvement should be included.

Response: The last three paragraphs of the Conclusions cover various approaches for future work, including expanding the data sample size, applying data-driven techniques, and modifying the wind speed bin definition. According to the reviewer’s comment, we modified the following in the Conclusions (lines 555 to 560):

“This work serves as a foundation for the progress to come. Looking forward, the lessons learned through the Share-3 exercise suggest possible activities for the next phase of the PCWG’s intelligence-sharing initiative. Specifically, new trial methods involving more comprehensive PDMs based on broad data sets, machine learning, and data from remote-sensing devices (RSDs) could be applied and tested. Corresponding to the growing popularity of RSDs, we should increase the volume of RSD-based data sets and thus the statistical significance of the analysis in future iterations of the PCWG intelligence-sharing initiative.”

Moreover, when we discuss the limitations of different methods in Appendix A1, A4,

A5, and A6, we also include proposed changes and additions to the trial methods in future iterations. In this manuscript, we want to focus on the results from this Share-3 exercise and spend a modest amount on potential future endeavors.

5. In appendix A2, when describing the Den-Turb correction method, at point 2.2.3. the definition of a 0-TI power curve is ambiguous. In particular, the authors state that “each WS is expanded to a Gaussian distribution, where the standard deviation is the product of the WS and the reference TI”, which is not clear since a 0-TI power curve is being calculated.

Response: Thank you for raising a great point, and your comment increases the reproducibility of this work. Step 2, which describes the derivation of a zero-TI power curve, is now edited and expanded, from lines 626 to 653:

"2. Calculate the initial zero-TI PC

2.1 Use the reference PC to:

2.1.1 Calculate the available power for the specific rotor geometry using the cubic relationship between WS and power; the resultant available power should always be larger than the reference power at each WS

2.1.2 Identify the four reference-PC parameters: the cut-in WS, the rated power, the rated WS, and the maximum cp

2.2 Use the four reference-PC parameters as inputs to construct a zero-TI PC for each WS:

2.2.1 For WS below the input cut-in WS, assign zero power

2.2.2 For WS above the input rated WS, assign the input rated power

2.2.3 For other WS, preserve the cubic dependence of power on WS and use the input cp to calculate power. At each WS, the zero-TI power is the product of thee WS and the available power at the WS. To account for the impact of TI on WS variation, each

WS is expanded to a Gaussian distribution, where the standard deviation is the product of the WS and the reference TI. The resultant expected power at each WS is the sum of products between the zero-TI power and the WS distribution.

2.3 Determine the resultant PC parameters

2.3.1 For each WS, if the resultant expected power is larger than the 10% of the product of the rated power and the WS, then label the WS as cut-in WS

2.3.2 For each WS, divide the resultant expected power by the available power to calculate cp

2.3.3 Across WSs, select the minimum cut-in WS, the maximum power, and the maximum cp

2.4 If the resultant PC fulfills all three convergence criteria (when the cut-in WS, the maximum power, and the maximum cp converge to those of the reference PC):

2.4.1 Label that PC as the initial zero-TI PC, and select the four input PC parameters (the cut-in WS, the rated power, the rated WS, and the maximum cp) as the four initial zero-TI PC parameters

2.4.2 Otherwise, adjust the four reference-PC parameters as revised inputs, repeat steps 2.2 and 2.3 for a maximum of three times, or until the convergence criteria are met"

6. In appendix A3, when discussing the Den-2DPDM trial correction methods, the authors state “One limitation of the 2DPDM is that the correction does not apply to the wind speed or TI bins with zero data counts (i.e., unpopulated bins)” without elaborating on the reasons this happens, or indicating if a correction of the method is possible.

Response: This limitation of 2DPDM is caused by data availability. Lines 675 to 678 now read:

“One limitation of the 2DPDM is that the correction does not apply to the wind speed or

TI bins with zero data counts (i.e., unpopulated bins), and no correction would be made to the data in those bins. For instance, such drawback takes place when the wind-turbine locations used to derive the PDM rarely measure high wind speeds (Fig. 1 as an illustration). Hence, this correction becomes inapplicable for those inflow conditions.”

Per another reviewer’s comments, we added a brief discussion on this data availability-dimensionality problem of PDMs. Lines 705 to 708 now read:

“Note that increasing the number of data bins by switching from a 2DPDM to a 3DPDM spreads the data samples thinner, and smaller sample sizes in each bin could weaken the overall statistical confidence of the correction method (Lee et al., 2015). Therefore, methods such as the regression tree ensemble (Clifton et al., 2013) provide solutions for such dimension expansion problem.”

References

Clifton, A., Kilcher, L., Lundquist, J. K. and Fleming, P.: Using machine learning to predict wind turbine power output, Environ. Res. Lett., 8(2), 024009, doi:10.1088/1748-9326/8/2/024009, 2013. Lee, G., Ding, Y., Xie, L. and Genton, M. G.: A kernel plus method for quantifying wind turbine performance upgrades, Wind Energy, 18(7), 1207–1219, doi:10.1002/we.1755, 2015. Power Curve Working Group: PCWG 3rd Intelligence Sharing Initiative Definition Document. [online] Available from: https://pcwg.org/PCWG-Share-03/PCWG-Share-03-Definition-Document.pdf, 2018.

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