The authors would like to thank the reviewer for the valuable comments provided. The comments are answered below and the changes to the paper will be highlighted in green, while the changes which are answers common to all reviewers are highlighted in light blue.

Line 40: I don't understand this statement. Why are they equivalent?

Line 41 reworded as follows for clarity:

As the LiDAR is sited on the roof of a coastal tower, at a height of 20m above the mean sea level,, the 80m measurement height would be equivalent to an offshore wind turbine (WT) hub height of 100m above the sea surface.

Line 160: meandering?

Line 162:

Dynamic Wake Meandering Model

Line: 216: again, confusing

Clarified in line 250 as follows:

In this case the wind data measured by the LiDAR at a height of 80m, would be equivalent to a cumulative height of 100m above sea-level, which would be the hub height of the wind turbines in the windfarm. This is because the LiDAR is situated on the rooftop of a coastal tower at a height of 20m above sea level, as shown in **Error! Reference source not found.**~~Table 3~~.

Line 223: what was the % of data that could be used?

Inserted the below in line 261:

Following analysis and filtration of the wind speed data at the reference site, 98% of the data was considered as suitable for the creation of the model. The data at the reference site was all considered as suitable. Hence, the regression model was created using the concurrent 8616 wind speed and direction values. For the year 2015, 95.6% of the data was considered valid (the measurement campaign started on the 26th of June, 2015, hence there were 4368 hours of wind speed and direction measurement of which 4176 were valid data points).

Line 236: in a row

Line 280 changed as follows for a better clarification:

The windfarm is made up of 50 wind turbines. There are 10 wind turbines in a row, having a cross-wind spacing of five rotor diameters (5D). The distance between the successive rows of wind turbines, or the downwind spacing is eight rotor diameters (8D).

Line 278: So, if I understand correctly, an MCP model is made for wind speed. Then for wind direction, two more MCP models are created for the wind speed components, which are then used to calculate the wind direction. These latter two models could of course also be used to calculate the magnitude of the wind speed and compared to the first MCP model. Was that done? Is there an advantage of one approach versus the other? Please comment.

You understand correctly. This was done, but the results obtained with the first method (3 MCP models), were, by far superior to the second method (2 MCP models used to calculate the magnitude and direction of the wind). The reason why still remains to be investigated, and these results are not being presented in this paper. The scope of having three models, also possibly allows analysis of different combinations of MCP methodologies, i.e. using MLR for wind speed and ANN for wind direction. This was done for a limited number of combinations and is the subject of further research.

The results presented are those using 3 MCP models of the same type, and a comparison is thus made using four regression methodologies.

This paper is modified to reflect this in line 502, as part of the conclusion:

In this case, an MCP model was created for wind speed, and two more MCP models were created for wind speed components, which were then used to calculate the wind direction. Another possible method is to calculate the magnitude of the wind speed from the models used to calculate the wind direction. This was done, but, the results from the first method, were by far superior to those from the latter method. The reason why, still needs to be investigated as part of future work, and these results are not being presented in this paper. The advantage of having three models, also allows the possibility of using different combinations of MCP methodologies, i.e. using MLR for wind speed and ANN for wind direction. This was also performed for a limited number of combinations and is also the subject of further research.
Line 393: More info needed on how these values were calculated. i.e. what formulas, etc. **Also, would tables 5 and 6 be more informative if they were normalized by the wind farm capacity, or average power output of the farm?**

The residual values are being changed to normalised values, based on the average of the residuals. There the following paragraph is being introduced to show the formulas used to calculate the metrics. The formulas used to derive these metrics are inserted as follows:

Line 18:

The predicted power is compared to the power output generated from the actual wind and direction data by using the Normalised Mean Absolute Error (NMAE) and the Normalised Mean Squared Error (NMSE).

Line 44:

Thus, the NMAE, the NMSE and the percentage error in the overall energy yield are compared for the various methodologies and wind farm topologies.

Line 228

The results are compared by using the NMAE and the NMSE of the residuals, using the Eq (8) to Eq. (12). The residuals, e_i are the errors between the predicted and actual output power values from the windfarm,

$$e_i = P_i - P_{act_i} \tag{8}$$

The formula used to calculate the NMAE is shown in Eq. (9), whereby the errors are normalised by dividing by the average power production over the whole period of evaluation (Madsen, et al., 2005):

$$NMAE = \frac{\sum_{i=1}^{N} |e_i|}{\sum_{i=1}^{N} P_i} \tag{9}$$

And the Normalised Mean Square Error (NMSE) is given by:

$$NMSE = \frac{\frac{1}{N}\sum_{i=1}^{N}(e_i)^2}{\bar{P} \cdot \overline{P_{act}}} \tag{10}$$

where,

$$\bar{P} = \frac{1}{N}\sum_{i=1}^{N} P_i \tag{11}$$

and

$$\overline{P_{act}} = \frac{1}{N}\sum_{i=1}^{N} P_{act_i} \quad (12)$$

The percentage error in overall energy yield is given by Eq (13), where:

$$e_{eng} = \left(\frac{\sum_{i=1}^{N} P_i - \sum_{i=1}^{N} P_{act_i}}{\sum_{i=1}^{N} P_{act_i}}\right) \cdot 100\% \quad (13)$$

The nomenclature is modified accordingly:

Line 553:	e_i	Residual, *MW*
Line 552:	e_{eng}	Percentage error in energy yield
Line 550:	NMSE	Normalised Mean Squared Error
Line 545:	NMAE	Normalised Mean Absolute Error
Line 577:	N	Number of data points
Line 578:	P	Predicted power output from wind farm, *MW*
Line 579:	P_{act}	Actual power output from windfarm, *MW*

Thus tables 6 and 7 are modified as follows:

Table 1~~6~~: Summarised results for Normalised Mean Absolute Error by MCP methodology and windfarm capacity.

Normalised Mean Absolute Error				
Wind Farm Capacity	***MLR***	***ANN***	***DT***	***SVR***
250MW	0.505	0.502	0.572	0.544
200MW	0.502	0.499	0.565	0.539
150MW	0.492	0.482	0.545	0.532
100MW	0.484	0.472	0.537	0.515
50MW	0.510	0.547	0.573	0.558

Table 2~~7~~: Summarised results for the Normalised Mean Squared Error (NMSE) of the normalised residuals by MCP methodology and windfarm capacity.

Normalised Mean Squared Error				
Wind Farm Capacity	***MLR***	***ANN***	***DT***	***SVR***
250MW	0.977	1.004	1.170	0.082
200MW	0.956	0.979	1.123	1.052
150MW	0.912	0.938	1.056	1.002
100MW	0.834	0.868	0.960	0.917
50MW	0.789	0.884	0.930	0.890

Line 425: I am having a hard time interpreting the results. Fundamentally, I don't see how we should distinguish between the three metrics used - MAE, MSE, and percentage error. What

do they each represent, and why are they not essentially equivalent? A reader needs more information of how to interpret the results and why the three metrics are each important.
The equations for the NMAE, NMSE and percentage error are now included in lines 227 to 235. Results are now normalised. Many references describe the use of multiple metrics to judge the quality of regression statistics (Rogers, et al., 2005), and it is important to employ more than one metric (Santamaria-Bonfil, et al., 2016). The lower the value, the better the performance of the model. Hence, the model having the lowest NMAE and NMSE, have the best performance. NMAE and NMSE are used to quantify the performance of the models. While NMAE is suitable for describing uniformly distributed errors. It also reveals any average variance between the forecast value and the true value (Hu, et al., 2013). The NMAE gives the same weight to the errors, while the NMSE gives a larger weight to the larger errors, and avoids using the absolute value. The NMSE assumes that the errors are unbiased and follow a normal distribution. The percentage error in energy yield gives an estimate of the accuracy of the model in the long-term, as it is the difference of the sum of the total predicted energy generated over the period of evaluation, expressed as a percentage of the actual energy. Hence an evaluation of the three metrics is necessary to evaluate the quality of the models. **This is inserted in the paper in line 182 as follows:** Several metrics may be used to evaluate the accuracy of the models (Rogers, et al., 2005), and it is important to employ more than one metric (Santamaria-Bonfil, et al., 2016) to perform the evaluation. The lower the value of the metric, the better the performance of the model. In this case the NMSE and the NMSE were used to quantify the performance of the model. The NMAE is suitable to describe the errors which are uniformly distributed round the mean, revealing also the average variance between the true value and the predicted value (Hu, et al., 2013). The NMAE applies the same weight to the individual errors. The NMSE is a measure of the extent of the dispersion of the errors around the mean and gives a higher weight to larger errors. It assumes that the errors are unbiased and follow a normal distribution (Santamaria-Bonfil, et al., 2016). The percentage error of the energy yield gives an estimate of the accuracy of the model for predicting the total energy generated by the wind farm over the period of evaluation. Due to the fact the each metric has disadvantages that can lead to inaccurate evaluation of the results it is not recommended to depend only on one measure (Shcherbakov, et al., 2013)..

References

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