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Detection of Nacelle Anemometers Faults in a Wind Farm

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Abstract. Control of wind farms requires the acquisition of accurate wind speed data. Nevertheless there is no system able to control the small, long-term degradation of data registered by anemometers installed in wind turbines. In this report we have developed a method to evaluate the quality of the wind speed measurements with the minimum uncertainty. This evaluation is made comparing the data from anemometers of the whole wind farm to detect its degradation and other anemometer faults. To obtain low uncertainties an estimation method has been developed that allow selecting the more adequate wind speed data range in each nacelle anemometer.

Key words

wind speed estimation, anemometer degradation, wind power systems, uncertainty propagation, wind farm maintenance.

1. Introduction

The great technological advances allowed during the last years and the stable legal framework have led the wind energy promoters to install as many farms as possible. This tendency has led to the installed power being so high that new needs have arisen for a good operations and maintenance plan.

One of the main problems in the wind farm production control is the wind speed data quality. The wind speed data measured by anemometers installed at the nacelle are affected by the weather, the topography, different problems with data acquisition or the degradation of the instrument. Even so, there is hardly any system to control their correct operation over the time beyond the control of the power curve. Especially difficult to detect are the small long-term degradation of its performance.

To control this fact we have developed a method based on the comparison of the wind anemometers of the whole wind farm. The main idea is to estimate the wind speed data in the target wind turbine using the wind speed data of other wind turbines.

To carry out the selection of the reference wind turbines we have calculated the correlation between every wind turbine based on historic nacelle anemometer filtered data. This selection is based on the value of the correlation coefficient between instantaneous wind speed measurements for close anemometers. This is made inspired in field calibration techniques of anemometers [1], because a higher value of the correlation coefficient corresponds to a less wind speed deviation.

To estimate the wind speed deviations a linear regression model is considered for each direction sector, in a similar way to the Measure-Correlate-Predict (MCP) algorithm that is usually used in the wind industry to predict mean wind speed characteristics [2]. However a new factor has been introduced since an underestimation exists in the uncertainty determination because consecutive data cannot be considered independent [3]. In order to evaluate the global deviation a factor, which accumulates the speed deviation for a period of time, is computed. It allows the detection of problems in the anemometer performance, including long-term deviations, and even if they are small.

However, some speed ranges must be eliminated due to their low quality. The deviation factor has different uncertainty depending on the wind speed data range and the direction sector used in its computation. On the other hand, the less data are used, the more uncertainty we have.

In this paper, the uncertainty of the method is computed in function of the data range, finding the speed ranges that introduce the minimum uncertainty in the deviation factor. In this way if the target anemometer has a high deviation from the closest reference anemometers a problem with his performance is considered. With this information it is possible to make a new calibration or a substitution if it's necessary, allowing a better control of maintenance faults of wind turbines. The method has been tested using real data from 53 turbines in a wind farm and the results are promising.

2. Deviation model

A. Studied Variables

To study the anemometer performance the deviation between anemometers is going to be estimated. The deviation between the wind speed registered in the target anemometer and reference anemometer is called RV_{xyi}, and it is defined as follows:

$$RV_{xyi} = \frac{V_{xi} - \hat{V}_{xi}}{\hat{V}_{xi}} \tag{1}$$

Where V_{xi} is the wind speed in target anemometer *x* and $\hat{V}_{xi}$ is the estimated wind speed in this target anemometer using the wind speed measured by anemometer *y*, and both considering a mean of the 10-minute interval *i*.

This instantaneous deviation obtained from the measured speed in other nacelle is very noisy and it can not be directly used. Besides that, the goal of the method is to detect long-term deviations. Therefore a temporal mean over a long period is considered. In the wind power industry, the wind farms development companies usually use monthly data to evaluate its performance and decide maintenance changes. So, we use as figure of merit the mean relative deviation in a month, $R\bar{V}_{xy}$.

To estimate the target wind speed, $\hat{V}_{xi}$, a linear regression model is considered for each direction sector, in a similar way to the Measure-Correlate-Predict algorithms that are usually used in the wind industry to predict mean wind speed characteristics for estimating the long term wind regime at potential wind farm [2]. The model to relate wind speeds of anemometers located in close nacelles is the linear least squares fitting [4]. The linear least squares fitting technique is the simplest and most commonly applied form to obtain a model from a set of points.

B. Uncertainty

Once the model is defined it's necessary to determine its uncertainty. There are no standard rules or methods for estimating the uncertainty. This can lead to a considerable range of variation in uncertainty estimations by different models [5], [6].

This study considers two important uncertainty sources in energy production estimations: the MCP and the anemometer. To calculate the model uncertainty, the error propagation formula [7] is repeated until obtaining the output uncertainty. So if an output variable *y* is computed using input variables, denoted by x_i, as

$$y = f(x_i) \tag{2}$$

the output uncertainty is calculated with

$$\sigma_y = \sqrt{\sum \left(\frac{\partial f}{\partial x_i}\right)^2 \cdot \sigma_{x_i}^2} \tag{3}$$

The least squares fitting uncertainty has been calculated as A. Derrick details [2], using the variances and covariance of the slope and offset.

When the estimated wind speed uncertainty has been calculated the deviation uncertainty in each 10-minute data is calculated with the next equation:

$$\sigma_{RV_{xyi}}^2 = \left(\frac{1}{\hat{V}_{esti}}\right)^2 \cdot \sigma_{V_{esti}}^2 + \left(\frac{V_{esti}}{\hat{V}_{esti}^{\,2}}\right)^2 \cdot \sigma_{\hat{V}_{est}}^2 \tag{4}$$

And the deviation uncertainty in a month, or in another period of time, is calculated as follows

$$\sigma_{R\bar{V}_{xy}} = \frac{1}{n}\sqrt{\sum_{i=1}^{n} \sigma_{RV_{xyi}}^2} \tag{5}$$

3. Data used for analysis

In this study, a 53 wind turbine wind farm has been used to test the model. The data has been measured from June of 2007 to July of 2008 but due to confidentiality issues it is not allowed to be presented in detail.

As is well know in the wind power community [2], [8] it is necessary a long-term period data, at least 9 months, to have an accurate estimation of the wind speed when you correlate between two meteorological towers installed in different sites. For this reason, and to have a complete model of the wind farm performance, a whole year has been selected to fit the equations of the linear least squares fitting method. This period covers the first 12 months, from June of 2007 to May of 2008, and has been manually filtered by experts to delete the errors in the recorded data.

We are interested in comparing the wind speed measured from anemometers installed in nearer wind turbines and, as stated in [1], there is a relation between correlation coefficient and wind speed deviation. So, we have chosen the reference wind turbines based in the correlation coefficient. For each target wind turbine we have used two reference wind turbines with the highest correlation coefficient. This multiplicity allows avoiding that, in the case one reference wind turbine is affected, an incorrect deviation in target anemometer were calculated. The correlation coefficient has been calculated with the whole year data.

The model has been applied to the other two months available, June and July of 2008, in order to analyze it. In the studied case, because of the absence of information for the installed anemometers, a 0.1 m/s uncertainty has been considered as indicated in the product catalogues consulted.

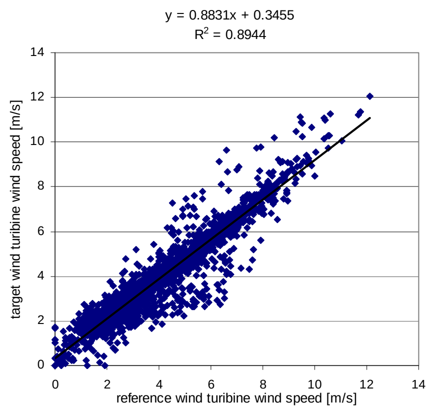
Due to the uncertainty of the lower speed data range and because it doesn't affect to the wind generator performance, we work with wind speeds greater than 2.5 m/s to make the studies.

4. Results and discussion

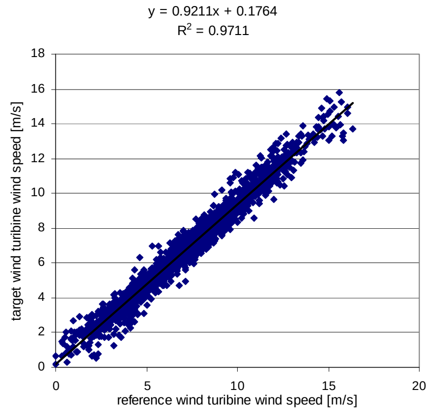
A. Direction sectors

To estimate the wind speed at target wind turbines a linear least square fitting is applied. In this way the $R\overline{V}_{xy}$ values obtained will be lower and more sensible to anemometer deviations.

It is well known in the wind power community that the influence of the direction in the wind flows is important, especially in complex terrain sites [9] [10] [11]. For this reason we have made a discretization into sectors of direction to calculate the fitting equations. As an example the figure 1 shows the relation between the wind speeds of two close anemometers in two different direction sectors.



a)



b)

Fig. 1. Relation between wind speed of anemometer 5 (horizontal-axis) and wind speed of anemometer 6 (vertical-axis) in a) the direction sector 2 and b) the direction sector 3.

B. Uncertainty estimation

To probe that the higher the wind speed is, the lower the deviation uncertainty is, the deviation uncertainty per bin has been calculated. However the Derrick model used to estimate the uncertainty in linear regression [2], underestimates the uncertainty [4]. The reason of this underestimation is that consecutive sets of wind speed data cannot be considered statistically independent [3].

In figure 2 the range of the real uncertainty that may be encountered has been represented. The striped line represents the standard deviation per bin of RV_{xy} in one month while the continuous line represents the mean of the uncertainty per bin of RV_{xy} in one month with the standard considerations to calculate the wind speed uncertainty.

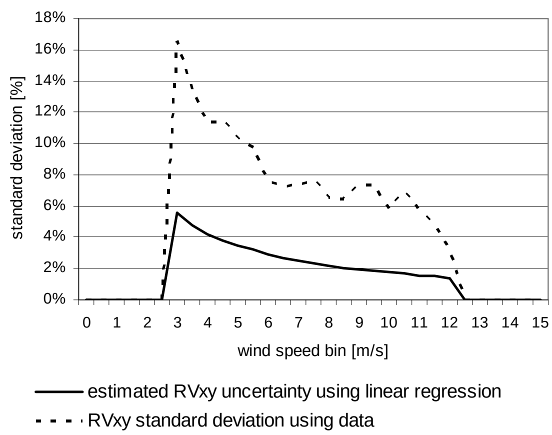


Fig. 2. Comparison between the mean of estimated RV_{xy} uncertainty of June 2008 and RV_{xy} standard deviation of June 2008 in each wind speed bin.

It can be seen that both, the estimated uncertainty and the real standard deviation, decrease when the wind speed increases. However the estimated uncertainty by the model is lower than it was expected.

To approximate the estimation to the real uncertainty the wind speed uncertainty has been multiplied by a factor of 10 to compensate that the 10-minutes wind speed averages can't be considerate statistical independent [4]. As shows figure 3 the approximation is adequate.

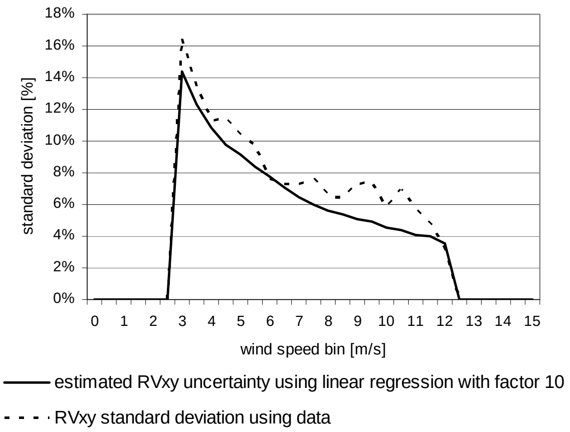


Fig. 3. Comparison between the mean of estimated RV_{xy} uncertainty multiplied by 10 of June 2008 and RV_{xy} standard deviation of June 2008 in each wind speed bin.

C. Minimal Uncertainty

As shown above, at higher wind speeds corresponds lower RV_{xy} uncertainty values. Therefore if the monthly deviation is calculated with the higher wind speeds we can expect to have an estimation with less uncertainty. Nevertheless, in this range of wind speeds the number of data is small, as shows figure 4. So, the sole use of high speed data will produce worse accuracy in the method. Therefore we have a trade-off between the number of measures and the wind speed range to leave the best deviation estimation.

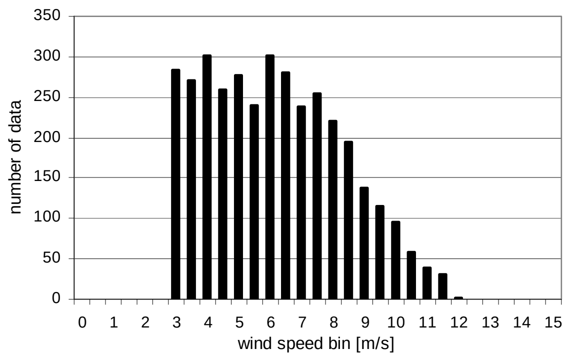


Fig. 4. Number of data per bin at wind turbine 5 in June 2008

To calculate the range wind speed that allows obtaining the minimum uncertainty in the deviation factor, the uncertainty of the average deviation per month has been calculated. In each average value computation the lower wind speed bin has been eliminated to find the range that has the minimum uncertainty. The results are shown in figure 5, which represents the monthly mean of estimated RV_{xy} uncertainty of the first 12 months to different data sets. The x-axis represents the minimum wind speed bin of the data set.

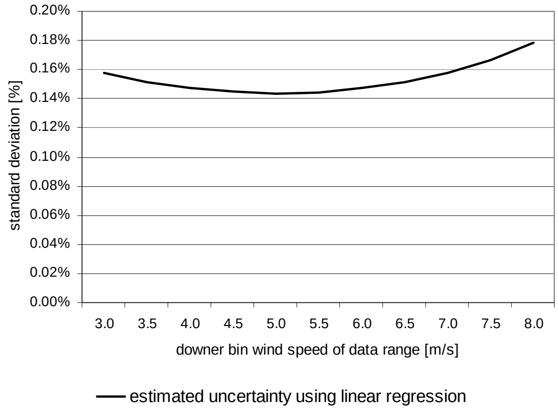


Fig. 5. Monthly mean of 12 months of estimated RV_{xy} uncertainty in data sets with different wind speed ranges.

In figure 5 it can be observed how there is a bin where the uncertainty is the lowest. If we studied the wind speed deviation with the data greater than this bin the uncertainty will be the minimum.

However, we can't estimate the monthly uncertainty of RV_{xy} just by applying the error propagation formula because the ten-minute data can't be considered statistical independent as we saw before.

To estimate correctly the uncertainty we have made a test dividing the number of data by different factors to approximate it to the real standard deviation. The most adequate factor that allowed estimating the uncertainty was 5, as shows figure 6.

In figure 6 is represented the monthly mean of estimated RV_{xy} uncertainty of 12 months multiplied by 5 and the RV_{xy} monthly mean standard deviation of the 12 months to different data sets. The x-axis represents the minimum wind speed bin of the data set.

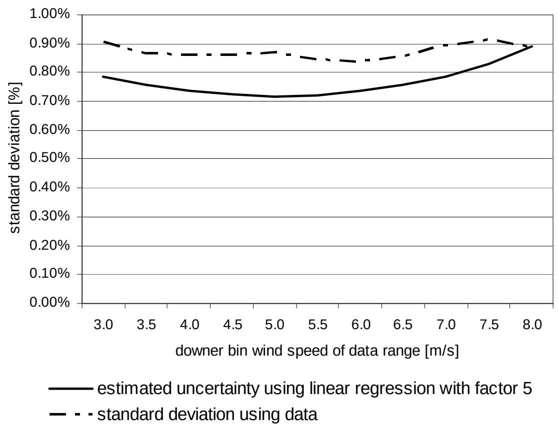


Fig. 6. Comparison between the monthly mean of estimated RV_{xy} uncertainty of 12 months multiplied by 5 and RV_{xy} monthly mean standard deviation of 12 months in data sets with different wind speed ranges.

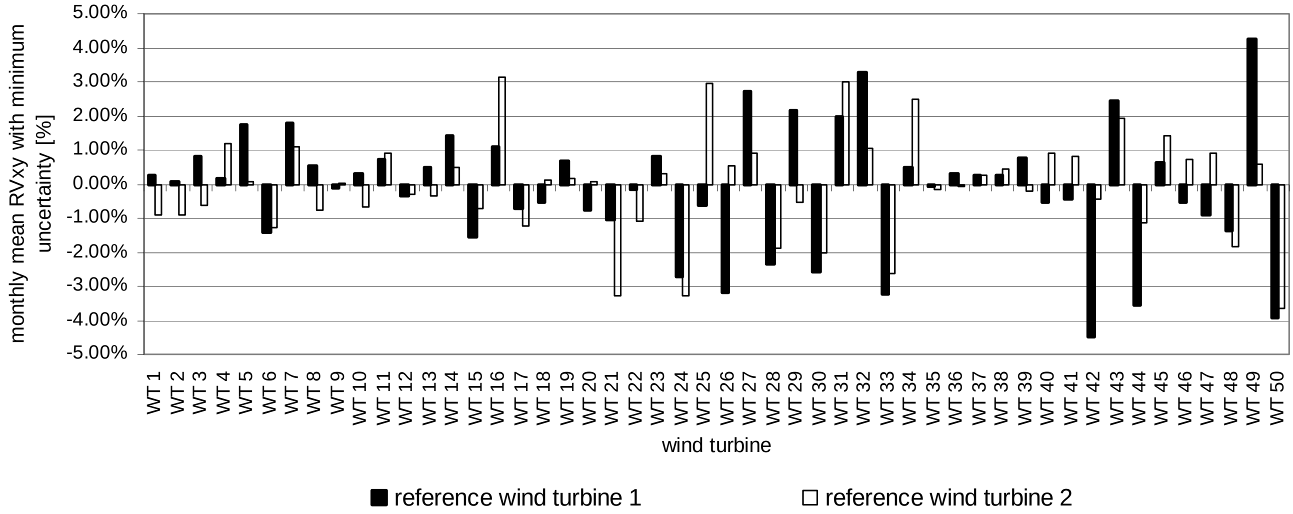


Fig. 7. Monthly mean RV_{xy} with minimum uncertainty for each wind turbine with regard to two reference wind turbines. Results of January 2008

D. Final results

Once the uncertainty model is defined the last step is to determine the maximum value of monthly mean RV_{xy} which will be considered as acceptable in an anemometer performance. To determinate this maximum value it has been calculated the monthly mean RV_{xy} with minimum uncertainty of each one of the 12 first months which has been filtered. The calculation has been realized with each target wind generator and two near anemometer.

The results of one of this filtered month can be seen at figure 7.

The results show that there isn't any wind turbine whose deviation is higher than 4% with regards to both reference wind turbines. In the other 12 months the results are similar.

Then the methodology to control the performance will be to calculate the deviation with higher correlation anemometer, or reference 1, if the value of the monthly mean RV_{xy} with minimum uncertainty is less or equal than 4%, it will be considered that the performance is correct. In the case the value is higher, a calculation of the monthly mean RV_{xy} with minimum uncertainty with reference anemometer number two is necessary. If the comparison with both references is higher than 4% it will considered that the anemometer suffers a deviation. In other cases, the anemometer performance will be considered correct. This simple criterion is expected to be improved in future work.

Finally it has checked this value in the non-filtered months to determinate if any of the anemometer wind turbines work correctly. The results are in the table below.

TABLE II. - $R\bar{V}_{xy}$ values with minimum uncertainty regards to two reference wind turbines in June 2008

Target wind turbine	Ref 1	$R\bar{V}_{xref1}$	Ref 2	$R\bar{V}_{xref2}$	Performance
WT1	WT2	-0.29%	-	-	✓
WT2	WT1	0.54%	-	-	✓
WT3	WT2	0.77%	-	-	✓
WT4	WT5	0.19%	-	-	✓
WT5	WT6	-4.37%	WT7	-5.01%	☒
WT6	WT7	-0.44%	-	-	✓
WT7	WT6	0.06%	-	-	✓
WT8	WT7	-7.56%	WT9	-3.33%	×
WT9	WT8	1.70%	-	-	✓
WT10	WT9	1.37%	-	-	✓
WT11	WT12	5.47%	WT10	2.75%	×
WT12	WT11	-5.32%	WT13	-1.03%	✓
WT13	WT12	0.35%	-	-	✓
WT14	WT15	0.70%	-	-	✓

Table II shows that the anemometer 5 presents an important deviation of its wind speed measurements regards to both reference anemometers. Therefore it is necessary a control of the performance of the machine and being careful with the wind speed data.

In the anemometer 8, 11 and 12 we found a deviation greater than 4% with the first reference anemometers. But in the second reference anemometer the deviation are inferior to the limit and will be considered that work correctly. Even so, due to the high value of deviation in the anemometer 8 and 11, it will be necessary to be carefully with these measurements too.

The results of the whole wind farm show that most of the wind turbines show deviation lower than 3% at least in one of the reference wind turbines. In every case the minimum deviation uncertainty is comprised between 0.65% and 0.85%.

5. Conclusions

In this paper we have defined a method, by the comparison of data captured by a nacelle anemometer against other anemometer in its vicinity, to control the degradation of the anemometer and erroneous performances. This method is run with a selected range of data which allows obtaining results with low uncertainty.

The selection of the range of data is obtained with a uncertainty model studied in this paper. This model show that the deviation has lower uncertainties when we works with wind speed data greater than 4 or 5 m/s.

Besides here an acceptable maximum value of deviation to determine if the anemometer performance is correct has been introduced.

References

[1] Paulsen, U.S.; Mortensen, N.G.; Hansen, J.C.; Said, U.S.; Moussa, A. E.-S., “Field calibration of cup anemometers”, in Conference proceedings (online) 2007 European Wind Energy Conference and Exhibition, Milan (IT), 7-10 May 2007. (EWEA, Brussels, 2007)

[2] A. Derrick, “Development of the Measure–Correlate–Predict strategy for site assessment”, in Proceedings of EWEC '93 (1993)

[3] Kristensen, L. et al.: “Field Calibration of Cup Anemometers”, Risø-R-1218(EN), 2001

[4] A. Rogers, J. Rogers and J. Manwell, “Uncertainties In Resuts of Measure-Correlate-Predict Analyses”, in American Wind Energy Association, 2005

[5] Matthew A. Lackner, Anthony L. Rogers, James F. Manwell, “Uncertainty Analysis in MCP-Based Wind Resource Assessment and Energy Production Estimation” in Journal of Solar Energy Engineering (August 2008), Volume 130, Issue 3

[6] Mark A Taylor, Pawel Mackiewicz, Michael C. Brower, Michael Markus “An Analysis of Wind Resource Uncertainty in Energy Production Estimates” in EWEC 2004

[7] EA Publication. “Expression of the Uncertainty of Measurement in Calibration”, EA document EA-4/02; 1999. 79 p.

[8] Rogers, A. L., Rogers, J. W., Manwell, J. F., “Comparison of the Performance of Four Measure-Correlate-Predict Algorithms”, Journal of Wind Engineering and Industrial Aerodynamics, Vol. 93/3, pp. 243-264, 2005

[9] Wood, N. “Wind flow over complex terrain: a historical perspective and the prospect for large-eddy modelling”. Boundary-Layer Meteorol. 96, 11–32

[10] A. Llombart, A. Mallet, N. Burillo, O. Alvarez and A. Talayero “Influence of orography on wind resource assessment programs” in EWEC 2007

[11] IEC 61400-12-1: Power performance measurements of electricity producing wind turbines, first edition 2005