# CORRELATION EFFECTS IN THE FIELD CLASSIFICATION OF GROUND BASED REMOTE WIND SENSORS

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Abstract

A classification scheme for remote sensing devices (RSDs) is included in the draft revision of IEC 61400-12-1 "*Power Performance Measurements of Electricity Producing Wind Turbines"* to enable the traceable assessment of uncertainty in RSD measurements. An assumption of the classification scheme is that the environmental variables (EVs) against which an RSD is classified are uncorrelated. The standard acknowledges that this assumption is not always valid and mitigation is permitted. A method for mitigation is however not included. The effect of correlation between environmental variables in the classification scheme is presented along with a method for mitigation that removes the duplicate uncertainty components caused resulting in a lower and it is proposed more representative uncertainty assessment for the RSD. Correlation between environmental variables in the classification test has the potential to produce increasingly unrepresentative uncertainty assessments in the verification and application tests following the standard as the wind conditions across the tests diverge. The impact of correlation between EVs in terms of the maximum theoretical total standard uncertainty (TSU) for the RSD is therefore also investigated. An accuracy class result in the range 3 – 7 is obtained for the lidar after mitigation with associated uncertainty in horizontal wind speed of around 2%. Consistent results are obtained across 44 verification tests and 20 application tests carried out using the classification. These place wind speed total standard uncertainty in the range 2-3% across the wind speed ranges tested in non-complex terrain.

# 1 Introduction

IEC standard 61400-12-1 [1] lays out guidelines for measurement of the power performance characteristics of individual wind turbines. Measurement of wind speed and quality parameters plays a central role in this process providing the baseline quantification of wind resource against which the performance of the turbine is assessed. The current edition of IEC 61400-12-1 only permits the use of cup anemometers of class better than 1.7A (2.5B or 1.7S in complex terrain) for the measurement of wind speed following the ACCUWIND scheme for the wind tunnel classification of cup anemometers [2]. Wind vanes are permitted for the measurement of wind direction. IEC 61400-12-1 is currently in the process of revision by the IEC TC88 maintenance committee. As part of this revision the use of remote wind sensing techniques, such as SODAR and lidar, is to be permitted under certain conditions. A requirement of the draft revision of the standard (IEC 61400-12-1 CD) is that the performance of remote sensing devices (RSDs) be classified in a similar manner to the classification of cup anemometers. This is required to enable a traceable assessment of uncertainty in the measured power curve to be made. In developing such a classification scheme for RSDs the main issue that has had to be accounted for is that at the present time there are no facilities or methods available with which wind tunnel testing can be achieved for RSDs in the configurations generally used for collecting ground based wind measurements. As such the RSD classification scheme developed for inclusion in the standard involves classification of devices in the field against cup anemometry. Details of the classification scheme are provided Annex L of the draft revision of IEC 61400-12-1 [3].

It is a fundamental assumption of the basic methodology of Annex L that the environmental variables (EVs) against which an RSD is classified and verified are statistically independent, i.e. uncorrelated. Where this assumption is valid any sensitivity observed against a particular EV can be entirely attributed to the influence of that EV on the RSD. The assumption that EVs are uncorrelated is however in general not valid and variables such as wind shear and turbulence intensity (TI) are very often strongly correlated. The effect of this on the classification scheme in Annex L is to duplicate uncertainties in the overall assessment of uncertainty for a particular RSD. This issue is acknowledged in the CDV and mitigated by permitting EVs to be removed from the classification test where it can be shown that the observed sensitivity for that EV is attributable to correlation with another EV that influences the performance of the RSD rather than the EV having an influence directly.

Presented here is a pragmatic method for the mitigation of correlation between EVs in the IEC RSD classification scheme. The method is tested for the classification of a ZephIR 300 wind lidar at the ZephIR lidar tall mast test site at Pershore in the UK [4] and the results of the mitigated classification test compared with those of the classification following the basic method as specified in [3]. The results of 44 verification tests and 20 application tests using the mitigated and unmitigated classifications are also presented for comparison.

Annex L in [3] comprises three distinct elements, the classification test, the verification test and the application test which is carried out during the power curve measurement campaign.

# 2 Classification Test

The classification test aims to quantify the systematic variation in the performance of a specific model of RSD with variation in environmental variables (EVs) such as wind shear and turbulence intensity and device specific factors such as data availability. The test is carried out by recording co-located measurements from an IEC compliant tall anemometer mast and the RSD over a period of time that captures significant variation in wind conditions. The relationships between systematic variation in performance and environmental variables are used to extrapolate device performance across wind conditions predicting the maximum likely deviation in RSD wind measurements at a site for which the environmental variables are at the extremes of their known variability. This maximum deviation sets bounds on RSD performance under all likely conditions of use and is expressed in a measure referred to as the *Accuracy Class* of the RSD. The method used for quantifying variation in device performance with variation in environmental variables is to perform a binned one-dimensional, two-parameter Ordinary Least Squares (OLS) linear regression of deviation in RSD wind speed measurement against each of the environmental variables under consideration. An example for wind shear is shown in Figure 1 a).

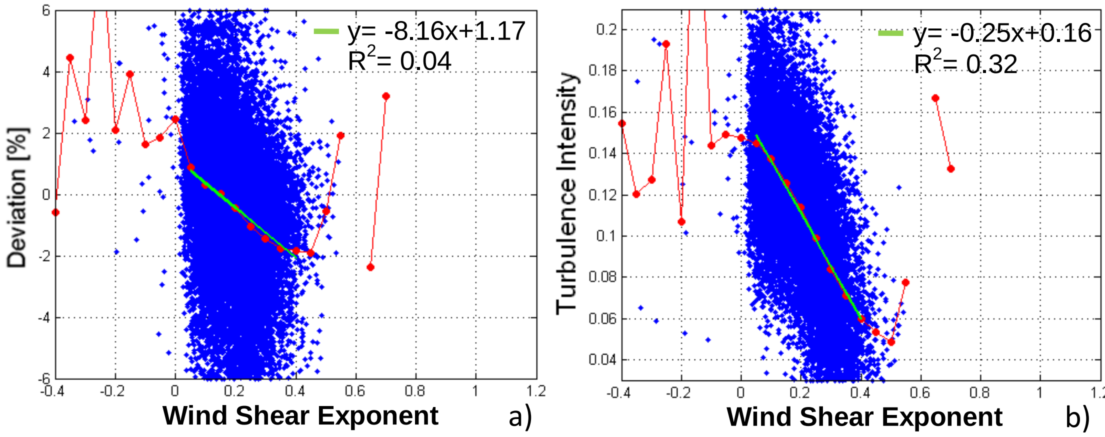


**Figure 1) a) Example Classification Regression**

**b) Wind Shear vs Turbulence Intensity at 91m AGL from lidar Test Site**

Where Deviation = 100*(RSD Wind Speed – Reference Wind Speed)/ Reference Wind Speed.

Reference wind speed here refers to the cup anemometer measurement from the mast. The bins to be included in the regression are screened with respect to their populations and the standard error of the mean to eliminate unrepresentative bins that may skew the regression. To estimate the maximum deviation in RSD measurement with variation in a particular EV the un-forced slope of the regression is multiplied by the range between pre-defined upper and lower limits for the maximum known variability of the EV. The Limits and ranges used in this classification test are presented in Table 1.

| | | Non-Complex Terrain | | |
|---|---|---|---|---|
| **Environmental Variable** | **Unit** | **Max** | **Min** | **Range** |
| Shear Exponent | [-] | 0.8 | -0.4 | 1.2 |
| Turbulence Intensity | [-] | 0.24 | 0.03 | 0.21 |
| Wind Direction | [°] | 360 | 0 | 180 |
| Air Temperature | [°C] | 40 | 0 | 40 |
| Air Density | [Kg/m^3] | 1.35 | 0.90 | 0.45 |
| Air Temperature Gradient | [°C/m] | 0.075 | -0.025 | 0.100 |
| Wind Veer Gradient | [°/m] | 0.25 | -0.25 | 0.50 |
| Inflow Angle | [°] | 3 | -3 | 6 |

**Table 1) Environmental Variable Ranges**

The result of this multiplication is referred to as the *Maximum Influence* of the EV. Selection criterion are applied to determine whether or not the maximum influence for a particular EV is included in the calculation of the accuracy class. This selection criterion is based on two measures. The first measure is referred to as the *Sensitivity* of the RSD for a particular EV and consists of the slope of the unforced regression multiplied by the standard deviation of the EV. This forms a normalised measure that expresses the amount by which the deviation between RSD and reference wind speed measurements is changed by a change of one standard deviation in the EV. The second measure consists of the sensitivity multiplied by the correlation coefficient (R) from the regression. If the sensitivity of the RSD to a particular EV is greater than 0.5 or the sensitivity x R is greater than 0.1 the EV is considered to have a significant influence on the RSD and is included in the accuracy class calculation. Where a number of measurement heights are involved in the classification, if an EV is determined to be included in the accuracy class calculation at any one of the measurement heights it must be included in the calculation at all measurement heights regardless of the assessment against the selection criteria at these other heights. The accuracy class for the RSD is then calculated by summing the maximum influence for each of the EVs under consideration in quadrature as they are assumed to be statistically independent.

## 2.1 Effect of Correlation Between Environmental Variables

A strong correlation between wind shear and turbulence intensity exists in the classification data set measured at the ZephIR lidar test site shown in Figure 1 b). Figure 2 a) shows the correlation between wind shear and turbulence intensity in the classification data set against deviation in wind speed measured by the lidar and cup anemometer. Figure 2 b) shows the data binned by wind shear.

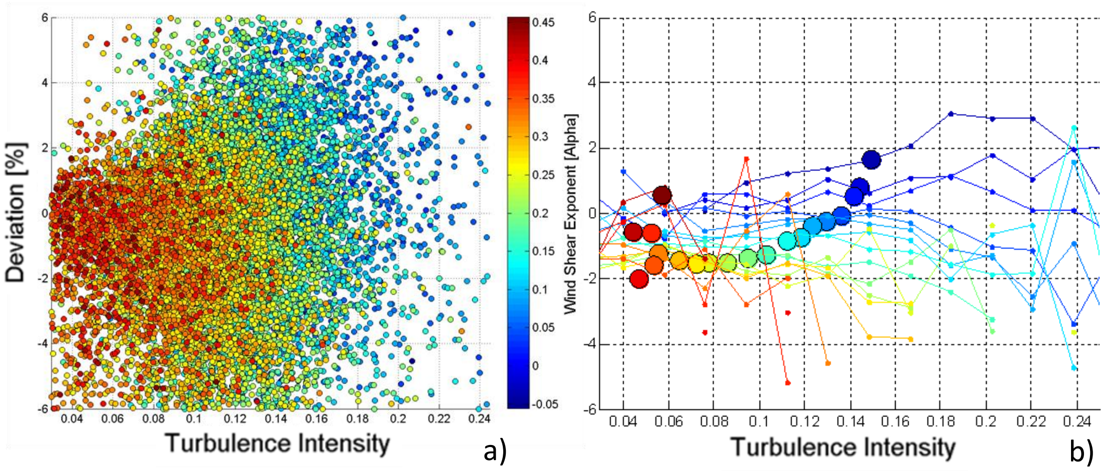


**Figure 2) Deviation vs TI vs Wind Shear at 91m AGL**
**a) Ten Minute Data, b) Data Binned By Wind Shear Exponent.**

It can be seen from Figure 2 a) that the data points are clustered along the TI axis according to the value of the wind shear exponent. This is due to the correlation between wind shear and turbulence intensity shown in Figure 1 b). A similar clustering would be observed for deviation vs wind shear coloured by TI. Where measurement deviation is systematically linked to only one of these EVs the clustering of the data in the regression for the other correlated EV will cause a sensitivity to be observed for that EV as well. The accuracy class of the RSD is accumulated from the multiplication of the slopes of the observed sensitivities by the ranges of the EVs. This means that a proportion of the uncertainty accumulated for an EV that does influence measurement deviation is accumulated again for any EV that does not influence measurement deviation but is correlated with the EV that does. Wind shear is known to influence measurement deviation for lidar and SODAR devices. Wind shear is also known to be correlated with other potential EVs in the classification scheme including TI, temperature difference (or gradient), wind veer, inflow angle, atmospheric stability and may also be related to wind direction due to site orography and topography. It is clear that where an extensive list of EVs that may be correlated to wind shear are included in an RSD classification there is the potential for over-estimation of device uncertainty due to the underlying assumptions of the classification scheme.

## 2.2 Method for Accounting for Correlation Between Environmental Variables

The following pragmatic method has been developed to mitigate for the effects of correlation between EVs in the classification scheme.

**Stage 1**

1. Select an EV.
2. Assess the correlation between this EV and the other EVs in the classification.
3. Form a group consisting of this EV and the correlated EVs.
4. Repeat steps 1 – 3 for the remaining EVs that are not in a group.
5. Repeat steps 1 – 4 until all EVs are in a group.

The assessment of the correlation between EVs in stage 2 may be carried out using a similar sensitivity method and criteria as in the classification scheme except with the selected EV as the abscissa variable. For each group select a base EV for which there is a known relationship between the EV and measurement deviation for the specific RSD or reference sensor. If there are no EVs that fit this criterion in a group then select any one of the EVs. Consideration of the statistical nature of any EVs included in the classification and verification scheme should be made when selecting base EVs and forming groups. This is particularly evident when including wind direction as an EV. The classification scheme defined in Annex L is based on Gaussian statistics. This assumes that an EV will have a mean value around which the distribution of values will be such that the standard deviation is a valid measure of dispersion. It also assumes that any relationship between measurement deviation and variation in an EV will be linear. These assumptions cannot be valid for wind direction as it is a circular variable. This is likely to lead to erratic results when classifying RSD performance against wind direction. Another problem linked to this is that the topography, orography and general wind climate is likely to vary systematically at the test site depending on wind direction. It is therefore likely that the relationship between measurement deviation and wind direction will vary due to correlation with other EVs in the classification but in a nonlinear way due to the circular nature of the wind direction measurement. As such, in compensating for correlation between EVs wind direction should be included in every group of EVs  but not as the base EV. For the ZephIR 300 classification data set and EVs this gives the groups shown in Figure 3 a).

**Stage 2 :**

Having grouped the variables and selected base EVs the relationship between the base EV in each group and measurement deviation should be established. This is done by binning measurement deviation with respect to the base EV and fitting a function to the binned data. This function need not necessarily be linear and a cubic polynomial often provides a good fit to any nonlinear relationships. The relationship between measurement deviation and wind shear for the ZephIR 300 classification data set at 91m AGL is shown in Figure 3 b). When combined with the relationship between wind shear and a grouped EV this relationship can be used to transfer deviation attributable to wind shear into the domain of the grouped EV. An example for turbulence intensity at 91m AGL using the relationship in Figure 3 b) is shown in figure 4 a). The systematic deviation due to wind shear can then be subtracted from the relationship between deviation and the grouped EV, Figure 4 b). This results in a reduction of the slope of the sensitivity for turbulence intensity from 16.3 to 6.0 reducing the sensitivity below the selection criteria and eliminating turbulence intensity from the classification result. Where a relationship between a base EV and measurement deviation is known for the reference sensor the same methodology may be applied. An example in the classification data for ZephIR 300 is the relationship between measurement deviation and inflow angle. Cup anemometers are known to be affected systematically by inflow angle. Figure 5 shows the documented relationship between deviation and inflow angle for the Risø P2546A cup anemometer used as the reference sensor at Pershore in the 91.5m West position [2]. Figure 6 a) shows the relationship between measurement deviation and inflow angle at 91m AGL for the ZephIR 300 data set. If the cup response in the range -3° - +3° is represented with a linear model and the deviation subtracted from the relationship between deviation and inflow angle for ZephIR 300 the results suggest that the observed sensitivity to inflow angle in the classification data set is entirely attributable to the response of the reference sensor, Figure 6 b). The sensitivity in this case is reduced to below the selection criterion eliminating inflow angle from the classification result.

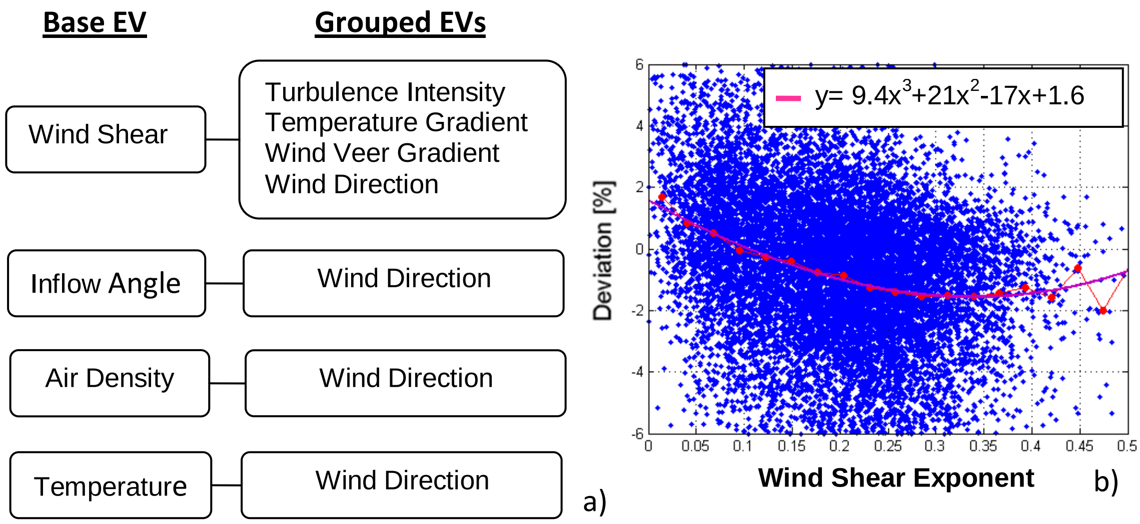


**Figure 3)** **a) Correlated EV Groupings**
**b) Deviation vs Wind Shear : Fitted Function at 91m AGL**

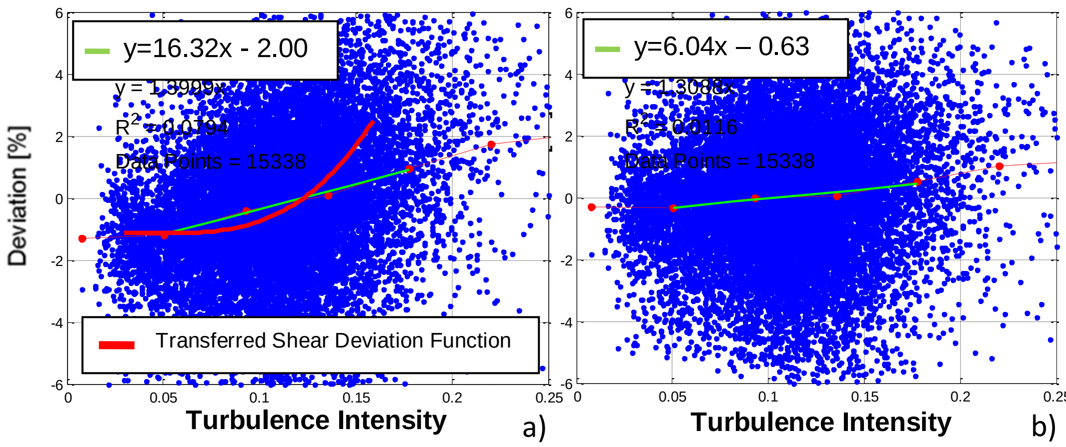


**Figure 4) De-correlation a) Transferred Shear Deviation Function**
**b) De-correlated Regression**

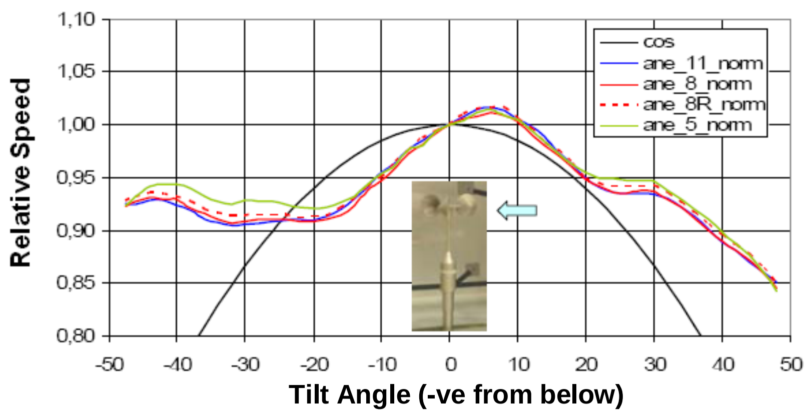


**Figure 5) Risø P2546A Cup Anemometer Inflow Angle Response Reproduced from [2].**

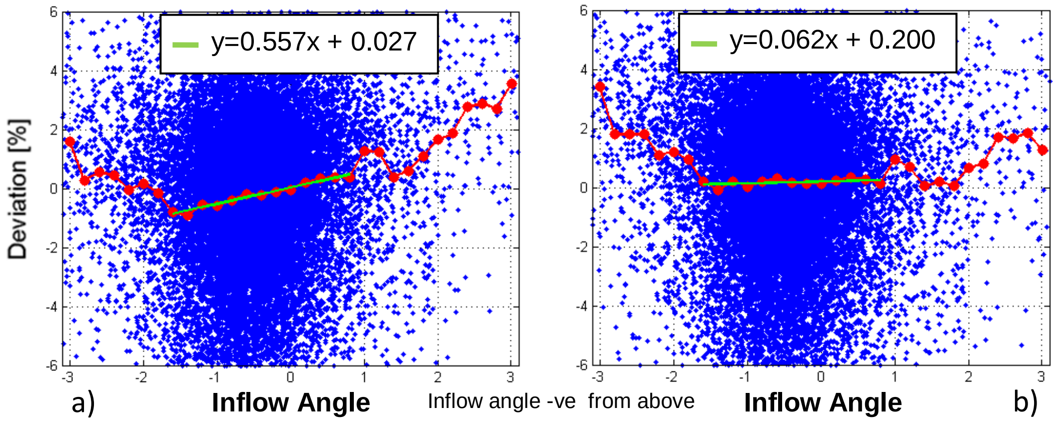


**Figure 6) Deviation vs Inflow Angle a) Measured b) Cup Response Removed**

## 2.3 Classification Results

A ZephIR 300 wind lidar has been deployed at the Pershore test site [4] as a long term reference for the analysis of lidar performance over time and with varying wind conditions. Sufficient data has been collected from this unit over a sufficiently long period of time to fulfill the data requirements for a classification test following Annex L in [3] at all measurement heights. The data set consists of approximately 4000 hours of data at four measurement heights between 20.5m AGL and 91.5m AGL in non-complex terrain. Performance of the ZephIR 300 has been classified against wind shear (α), turbulence intensity(TI), wind direction (Dir), temperature (T), temperature gradient (▽T), air density (ρ), wind veer gradient (▽Veer ) and flow inclination angle (FIncl). A classification that includes flow inclination can only be calculated at Pershore at the 91m measurement level as only this level on the mast is equipped with the 3-dimensional ultrasonic anemometer required to measure this EV. Sensitivities for the EVs under consideration are shown by measurement height with respect to the 0.5 limit for determination of significance in Figure 7 a).

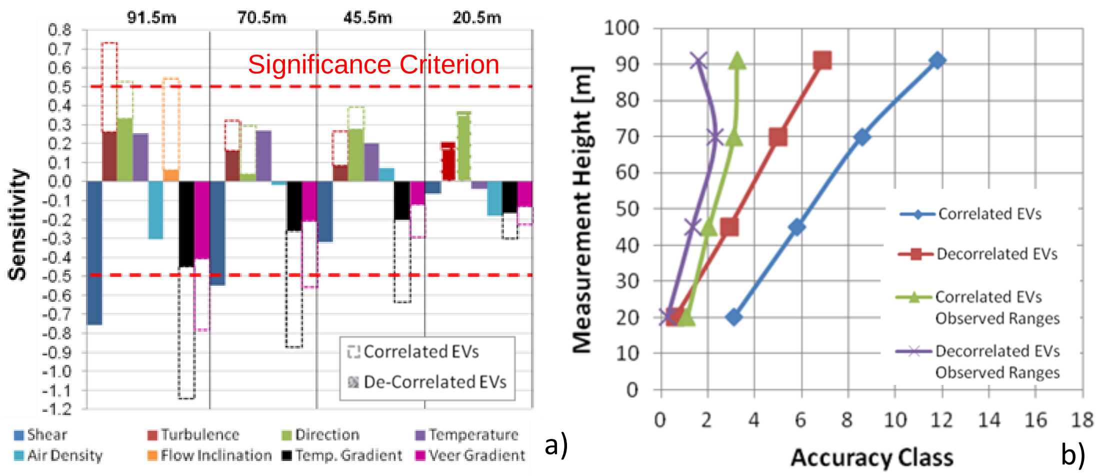


**Figure 7 a) Classification Sensitivities by Height, b) Accuracy Class Results**

The ZephIR shows significant sensitivities with respect to wind shear, turbulence intensity, wind direction, flow inclination, temperature gradient and wind veer gradient following the basic classification methodology in Annex L. Application of the de-correlation method in section 2.2 however eliminates all of the EVs correlated with wind shear from the classification result. Similarly, having removed the sensitivity contribution for inflow angle due to the response of the reference cup anemometer inflow angle is also eliminated from the classification result. This identifies wind shear as the only environmental variable that has a significant influence on the performance of the RSD. Similar results are obtained for the RxSensitivity criterion. Results are shown in Figure 7 b) for the classification calculated using the ranges in Table 1 and the ranges of the EVs observed during the classification test for comparison. Figure 7 b) suggests that where the correlation between EVs has not been accounted for, classification results from test sites or in periods with significantly different wind climates in terms of EV correlations are likely to produce somewhat divergent and incomparable classification results.

## 3 Verification Test

The verification test is carried out to confirm that a specific RSD unit performs according to the classified performance for that model of RSD. Annex L requires that 180 hours of data be available for an RSD verification test. Verification tests have been carried out for 44 ZephIR 300 deployments at the Pershore test site that fulfil this criteria. Example results for a single deployment at 91m AGL are included in Figure 8. In calculating the total standard uncertainty (TSU) for the verification tests the effect of terrain induced flow inhomogeneity at the Pershore test site has been assumed to be negligible due to the simplicity of the site terrain and orography. Mounting uncertainty for the RSD has been assumed to be 1%.Correlation between EVs can be seen in Figure 9 to have increased the sensitivity uncertainty that is associated with deviation in wind conditions between the classification and verification tests. This is because the slopes of the regressions from the classification test are used to calculate this uncertainty. As the total standard uncertainty is the sum of the other uncertainty components in quadrature, correlation between EVs has increased the total standard uncertainty for the RSD across the wind speed range. Combined results across all 44 verification tests are presented in Figure 10.

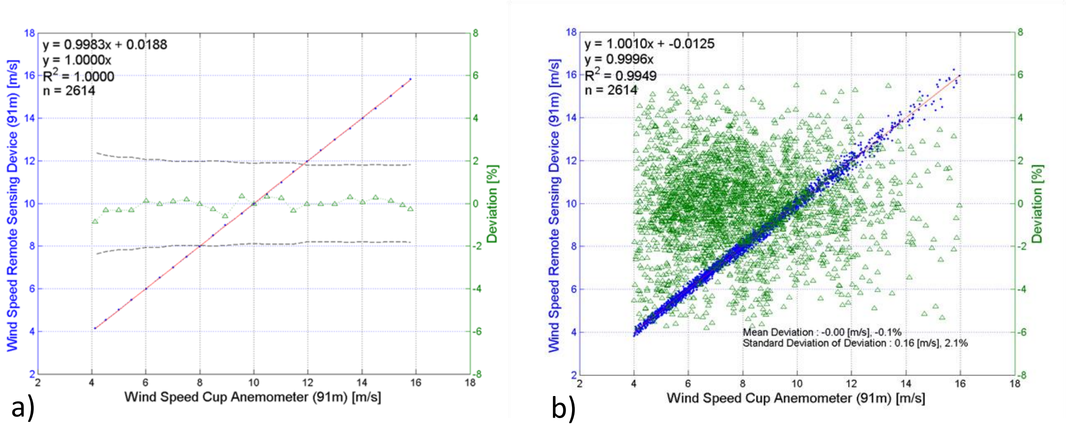


**Figure 8 Wind Speed Comparison, 91m AGL a) Binned b) Ten Minute Average**

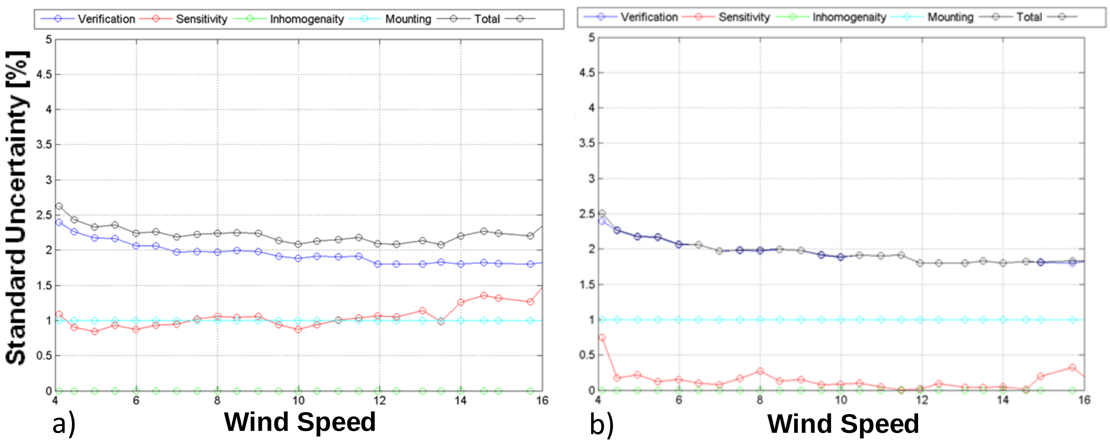


**Figure 9) Uncertainty Components a) Correlated EVs b) De-correlated EVs, 91m AGL**

Using the de-correlated EV classification slopes in the verification test results in a slight reduction in the TSU but not a significant one. This is because no significant deviation in the wind conditions is evident on average between the classification test and verification test as

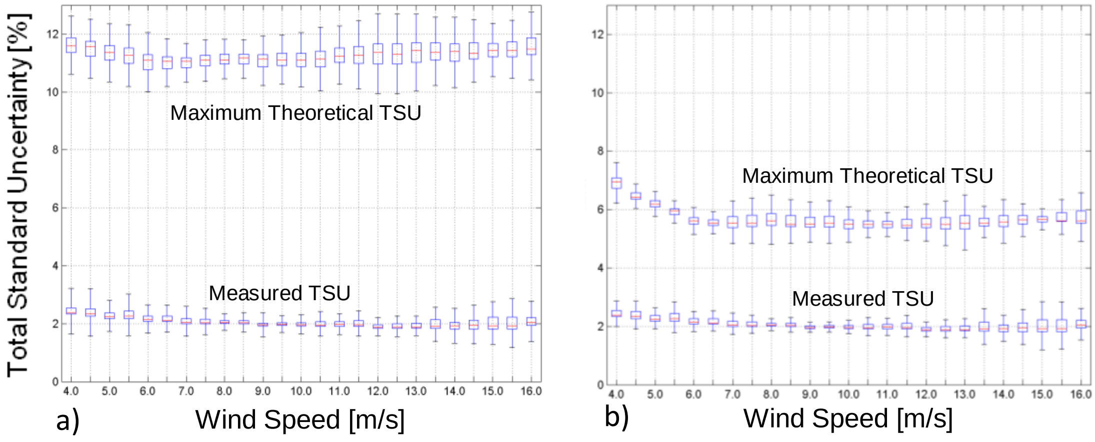


**Figure 10) 44 Verification Tests : Total Standard Uncertainty at 91m AGL**
**a) Correlated EVs b) De-correlated EVs.**

they occur at the same test site under similar climatic conditions. The potential effect of correlation between EVs becomes evident when the maximum theoretical TSU is calculated for the tests based on the ranges of the EVs in Table 1 used in the classification test as shown in Figure 10. The difference in maximum theoretical TSU in Figures 10 a) and b) is entirely attributable to correlation between EVs and is artificial. Results from verification tests based on classifications where correlation between EVs is not accounted for may therefore be divergent where the verification test takes place at a test site or in a period with significantly different wind climate in terms of EV correlations to that apparent during the classification test.

## 4 Application Test

Application tests have been carried out for 20 permutations of ZephIR 300 deployments at the Pershore test site where a verification from section 3 can be matched with another deployment of the same unit in a different time period. Application is simulated by using the mast measurement at 45m as the control mast measurement. Combined results across all 20 application tests are presented in Figure 11.

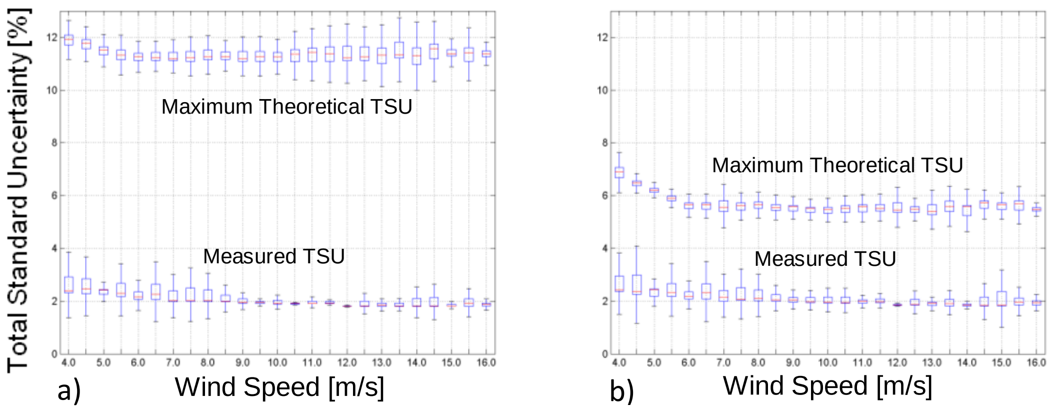


**Figure 11) 20 Application Tests : Total Standard Uncertainty at 91m AGL**
**a) Correlated EVs b) De-correlated EVs.**

Using the de-correlated EV classification slopes in the verification and application tests gives similar results to those for the verification test producing a slight reduction in measured TSU but with significant reduction in the maximum TSU by the same argument as for the verification test. The uncertainty components and total standard uncertainty at 10 m/s by height for ZephIR 300 across the 20 application tests are included in Table 2.

| | Uncertainty Component at 10 m/s [%] | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Verification** | **Sensitivity** | | **Control** | | **Inhomogeneity** | **Mounting** | **Total** | |
| **Height [m]** | **-** | **a)** | **b)** | **a)** | **b)** | **-** | **-** | **a)** | **b)** |
| 91.5 | 2.0 | 0.8 | 0.3 | 0.0 | 0.0 | 0.0 | 1.0 | 2.2 | 2.1 |
| 70.5 | 2.0 | 0.6 | 0.3 | 0.0 | 0.0 | 0.0 | 1.0 | 2.1 | 2.1 |
| 45.5 | 1.9 | 0.4 | 0.1 | 0.0 | 0.0 | 0.0 | 1.0 | 2.0 | 1.9 |
| 20.5 | 2.0 | 0.4 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 | 2.0 | 2.0 |

**Table 2 ) 20 Applications Tests : Mean Uncertainty Components at 10 m/s**
**a) Correlated EVs b) De-correlated EVs**

# 5 Conclusions

Correlation between environmental variables has been demonstrated to have a significant effect on the accuracy class result for a ground based remote wind sensor determined following the field classification scheme in Annex L of the draft revision of IEC 61400-12-1. This is due to an underlying assumption of the classification scheme rather than the performance of the remote sensing device. A practical method for accounting for the correlation between environmental variables has been presented. It is proposed that applying such a de-correlation method as part of the classification methodology will produce more representative and consistent classification results across different test sites and wind conditions. An accuracy class result in the range 3 – 7 was obtained for the ZephIR 300 wind lidar after de-correlation with associated uncertainty in horizontal wind speed of around 2%. Consistent results were obtained across 44 verification tests and 20 simulated application tests carried out against the classification. These place wind speed uncertainty at around 2% and total uncertainty in the range 2-3% across the wind speed ranges for the lidar tested in non-complex terrain. Although correlation between environmental variables was shown not to significantly affect the results of the verification and application tests this is attributable to the similarity of the wind conditions between the classification, verification and application tests due to the use of the same test site in similar time periods. It is demonstrated however that correlation between environmental variables is likely to affect the results of the verification and application tests as wind conditions across the tests diverge, potentially producing increasingly unrepresentative uncertainty assessments. The total standard uncertainty of an RSD following the IEC method is determined by adding an uncertainty to the uncertainty of the reference sensors against which the RSD is evaluated. This is of the order of between 1.5% and 2.0% depending on wind speed for a first class, calibrated, well mounted cup anemometer. The results above therefore show that across the entire wind speed range no significant additional uncertainty is attributable to the lidar over that attributable to the reference cup anemometers.

# References

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