Meteorologische Zeitschrift, PrePub DOI 10.1127/metz/2017/0826

Energy Meteorology

Comparison of methods for the identification of mesoscale wind speed fluctuations

Anna Rieke Mehrens* and Lueder von Bremen

ForWind – Center for Wind Energy Research, Department of Physics, Carl von Ossietzky University Oldenburg, Oldenburg, Germany

(Manuscript received September 19, 2016; in revised form November 30, 2016; accepted January 12, 2017)

Abstract

Mesoscale wind speed fluctuations influence the characteristics of offshore wind energy. These recurring wind speed changes on time scales between tens of minutes and six hours lead to power output fluctuations. In order to investigate the meteorological conditions associated with mesoscale wind speed fluctuations, a measure is needed to detect these situations in wind speed time series. Previous studies used the empirical Hilbert-Huang Transform to determine the energy in the mesoscale frequency range or calculated the standard deviation of a band-pass filtered wind speed time series. The aim of this paper is to introduce newly developed empirical mesoscale fluctuation measures and to compare them with existing measures in regard to their sensitivity to recurring wind speed changes. One of the methods is based on the Hilbert-Huang Transform, two on the Fast Fourier Transform and one on wind speed increments. It is found that despite various complexity of the methods, all methods can identify days with highly variable mesoscale wind speeds equally well.

Keywords: Energy Meteorology, mesoscale wind speed, Fourier filter, variability, Hilbert Huang Transform, North Sea, FINO 1

1 Introduction

Offshore wind speeds, and hence the power produced by wind turbines, fluctuate on different time scales. These fluctuations can be challenging for the grid integration of wind energy and electricity markets (e.g. Tande, 2003 or Georgilakis, 2008). Therefore, accurate short-term variability forecast would be beneficial (Foley et al., 2012). In order to achieve the goal of a day-ahead mesoscale variability forecast, automated fluctuation measures for specific time scales are needed to perform systematic studies on fluctuations in wind speed measurements. These wind fluctuation measures can be used to investigate seasonal patterns and physical interactions. Based on the results, a statistical forecast using numerical weather predictions can be developed.

Due to the characteristics of the wind turbine power curve, wind speed fluctuations are not directly transformed to power fluctuations. For fluctuative wind speeds higher than the cut-in and lower than the rated power, high power fluctuations are produced. For all wind speeds higher than the rated power, the power output should be more stable, despite wind fluctuations.

Meteorological phenomena can be classified in different temporal and spatial scales (Orlanski, 1975). The mesoscale is the scale where phenomena are smaller and faster than the synoptical scale 3 days and 1000 km), but also greater and longer than the microscale (1 h and 10 km). This paper will focus on mesoscale fluctuations with time periods between tens of minutes and several hours. Thus, 10 min wind speed measurements are used. The lower limit of frequencies, which are resolved, is given by the Nyquist frequency with a cycle duration of 20 min. The maximum mesoscale cycle duration is defined to be 6 h to exclude diurnal cycles.

Time scales on which wind speed is fluctuating can be visualized by a spectral power plot. Larsén et al. (2013) showed that a mesoscale phenomena like cellular convection at the offshore measurement site Horns Rev can clearly increase the spectral power in the mesoscale frequency range and thus lead to enhanced mesoscale variability.

A measure for mesoscale wind fluctuations should be sensitive to recurring wind speed changes on the chosen time scale. Ramp effects, which may lead to high one-time wind speed changes, should not be regarded. Furthermore, the computation time should be short to systematically analyze long term wind speed measurements.

Analyzing a specific time scale in a time series directly leads to spectral methods. Vincent et al. (2010) presented a wind fluctuation measure based on a statistical method called Hilbert-Huang Transform. Beside of the theoretical description of the method, they applied the method on measurements at the offshore measurement site Horns Rev and studied seasonal and diurnal patterns.

*Corresponding author: Anna Rieke Mehrens, ForWind – Center for Wind Energy Research, Department of Physics, Carl von Ossietzky University Oldenburg, Küpkersweg 70, 26129 Oldenburg, Germany, e-mail: anna.mehrens@forwind.de

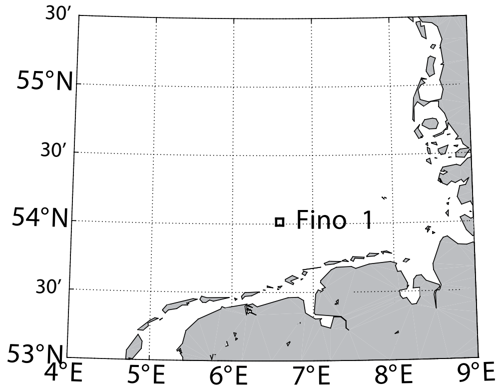

Figure 1: Location of the FINO 1 offshore met mast in the North Sea.

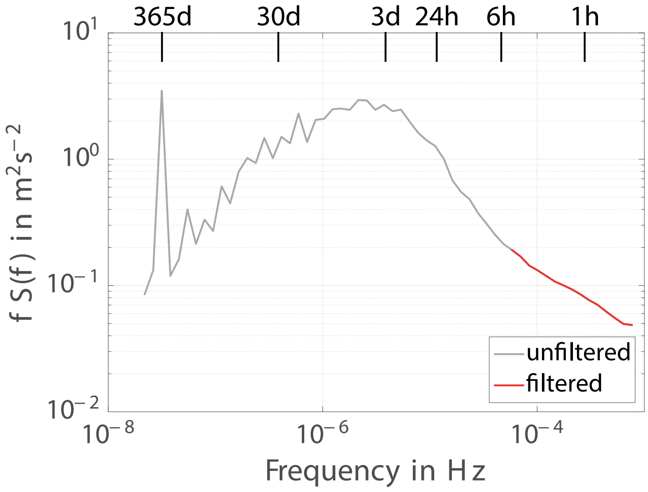

Figure 2: Spectral power of the FINO 1 wind speed measurement (black) and filtered measurements (red) from 2004–2016 in 100 m height.

In comparison, Davy et al. (2010) and Ellis et al. (2015) used the standard deviation of a running window applied to a band pass filtered wind speed or power time series to investigate the wind variability in south-eastern Australia. However, this method and the method of Vincent et al. (2010) have not been compared so far.

For the statistical characterization of wind turbulence, often wind speed increments are used (e.g. Morales et al., 2012 or Anvari et al., 2016). Nevertheless, increments have not been used for a time evolving mesoscale fluctuation measure before.

The aim of this work is to present newly developed empirical mesoscale fluctuation measures, which describe time dependent mesoscale wind variability, and to test and compare these with already existing ones. The preferable method should identify all situations with mesoscale wind fluctuations while using little computation time. To test the sensitivity of the measure to wind fluctuations we use the FINO 1 wind speed measurements presented in Section 2. All methods and the methodology for the comparison are introduced in Section 3. This section also includes first results for the individual measures and challenges of the application of the methods. For the comparison of the mesoscale wind speed measures in Section 4, the sensitivity to recurring wind speed changes is tested, the wind direction dependency is compared to the results of earlier studies and the computation time is calculated. The main conclusions are summarized in Section 5.

2 Observations

In order to test the mesoscale wind fluctuation measures, we use FINO 1 wind speed (100 m height, top anemometer) and direction measurements (90 m height) from 2004 to 2016. The wind speed time series includes 5.0 % missing values and the wind direction measurement 5.8 %. The location of the met mast in the North Sea is marked in Figure 1.

The top anemometer is surrounded by a lightning cage which influences the wind speed measurements. A comparison of the wind speed measurements in 100 m height with measurements in 90 m height shows that the lightning cage is decreasing the wind speed at the wind direction around 0°, 81°, 167° and 260°. Due to the focus on the fluctuations measures methods, these wind directions are not removed as this would result in a high amount of missing values. Nevertheless, the lightning cage seems to increase the mesoscale fluctuation measures for these wind directions (Section 4.2).

Methods which base on the Fast Fourier Transform (FFT) or Hilbert-Huang Transform (HHT) need a continuous time series, thus missing values are filled by linear interpolation using the last value before and the first value after the data gap. However, the respective fluctuation measure values of interpolated time series steps are not analyzed.

Figure 2 shows the spectral power of the wind speed measurements at FINO 1 in 100 m height, using the FFT. At the offshore met mast, most spectral energy is present in the yearly cycle and on the synoptical scale (3 days). The red line marks the time scale on which the spectral energy would be increased during mesoscale wind speed fluctuations. The mesoscale time scale was separated from the lower frequencies parts using a FFT filter.

3 Fluctuation measures

Figure 3 shows a wind speed measurement for February 2009. During this period of time, the wind speed fluctuates on different time scales. Because of our interest in mesoscale fluctuations only, the measure should not be sensitive to time scales greater than 6 h cycle duration. A 6 h maximum cycle duration is chosen to exclude daily cycles, which may be present in coastal wind speed measurements in lower heights than used here.

The fluctuation measure should be sensitive to recurring mesoscale wind speed changes. These are for exam-

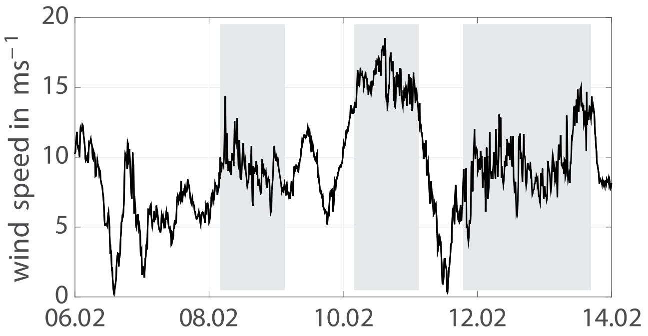

Figure 3: Wind speed measurement at FINO 1 in February 2009 in 100 m height. Time periods with mesoscale wind speed fluctuations are colored in gray.

ple present on the 8th, 10th and around the 12th of February at FINO 1. These days are highlighted in grey in Figure 3. It can be seen that during fluctuation periods the 10 min mean wind speed changes several times by more than 2 ms^{-1}. At the 10th and 11th, the wind speed shows increasing or decreasing trends, which are longer than the maximum cycle duration of 6 h. Consequently, the mesoscale fluctuations measure should not be sensitive to these. We will use this week of wind speed measurements to introduce the fluctuation measures.

When looking at a specific frequency range only, spectral methods are typically used. The kind of spectral method which is applicable depends on the time series characteristics. Vincent et al. (2010) discuss the non-stationarity of wind speed data and how to test it. They conclude that there are enough statistical and physical arguments for 10 min wind speed data to be non-stationary. Due to the non-stationarity of a wind speed time series, the use of a global spectral analyzes such as Fourier is questionable. In contrast, the empirical HHT can be applied to non-linear and non-stationary time series and is used by Vincent et al. (2010) as a mesoscale fluctuation measure.

Vincent et al. (2010) and Duffy (2004) discuss which other methods are available for analyzing non-stationary atmospheric time series. Vincent et al. (2010) decide not to use singular spectrum analyzes (e.g. Ghil et al., 2002) for analyzing the wind speed time series, as it is assuming an underlying periodicity. Additionally, Vincent et al. (2010) decided not to use Wavelet analyzes (e.g. Strang, 1989 or Barthlott et al., 2007) because of its dependency on the shape of the chosen wavelet function.

Despite the non-stationarity of a wind speed time series, we will use the FFT to develop two new empirical fluctuation measures and compare them with the results of the HHT and one new fluctuation measure based on increments. These fluctuation measures will be presented in the following subsections. The last subsection describes the applied standardization of the wind fluctuation measures, which is used for the comparison. All fluctuation measure values shown in the next chapters are standardized (Section 3.5).

3.1 Hilbert-Huang spectrum

Vincent et al. (2010) presented a wind fluctuation measure based on the HHT. The advantage of the empirical HHT is, that it is an adaptive spectral analyzes. It is a local method based on a non-parametric and empirical decomposition of the data and can be applied to non-linear and non-stationary data. Like the FFT, the HHT can be used for the investigation of either spatial or temporal frequencies. Also spectral analyzes like the spectral power plot in Figure 2 can be conducted based on the HHT.

The calculation of this fluctuation measure is based on Vincent et al. (2010) and the Matlab packages of RCADA (2015). We use the eemd-function, significance and nnspe-function of the RCADA (2015) toolbox. Detailed descriptions of the method are published in Huang and Wu (2008).

The eemd function (Ensemble Empirical Mode Decomposition, based on Wu and Huang (2009) is decomposing the time series into a set of intrinsic mode functions (IMF). The significance function (based on Wu and Huang, 2004) is testing the significance of each IMF against white noise. Finally, the nnspe function (based on Huang et al., 1998) calculates the Hilbert Transform of each IMF and the instantaneous amplitude and frequency. The resulting quantity is the Hilbert-Huang spectrum of energy. This spectrum is then multiplied by its frequency to emphasize high frequencies. For the comparison with other scalar measures, the energy of the desired mesoscale frequency range is summed up. This leads to a time series of the integrated mesoscale energy in the wind speed time series.

According to Huang and Wu (2008), the main limitations of the HHT are that it is an empirical method which has no mathematical justification other than the FFT. However, it has already been tested for a lot of applications. Huang and Wu (2008) state that further research on the HHT should focus on the optimization of the selection of the spline, the selection of the IMF and on the end effects. Another disadvantage of the method is the complexity which results in the longest computation time of all presented mesoscale wind speed fluctuation measures.

The end effect results in significantly high energy values for start and end of the time series, due to the envelope divergence at these points. The end effect is likely to cause problems for a real-time calculation of the fluctuation measure.

In this study, some high energy values occur, most of them with wind flow directions influenced by the lightning cage. Considering the relative frequency of the HHT values (Figure 8), all amplitudes higher than 60 ms^{-1} before the standardization are regarded as outliers.

3.2 Variance

The variance is a well known measure to describe how large the spread of a time series is around its mean value.

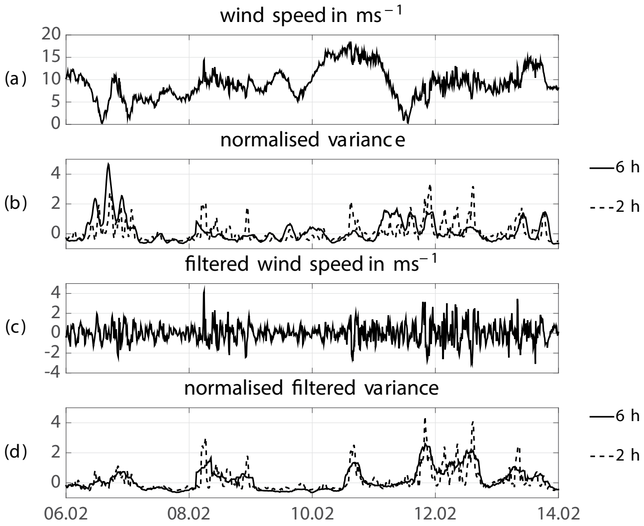

Figure 4: Running window variance of the wind speed for different time period (2 h and 6 h in February 2009), using filtered and unfiltered wind speed time series.

Because of our interest in the actual variance of several time steps, we calculate a running window variance. Therefore, we use the wind speed measurements of a specific time period before and after the actual time step and calculate the variance (*var*, Equation 3.1).

$$var = \frac{1}{n-1} \sum_{i=1}^{n} |x_i - \overline{x}|^2 \qquad (3.1)$$

With index i for each time step in the chosen time period with length n. The variance is calculated for a running window and we thus have a fluctuation measure value for each time step.

Figure 4(b) shows the running window variance for two time period lengths (n) of the wind speed time series shown in Figure 4(a). As expected, the variance gets smoothed with an increasing time period. Because the variance is calculated based on the wind speed time series, the fluctuation measure still includes all kind of fluctuations on all scales, which are included in the time series. Thus, variance can not yet be applied to measure mesoscale wind speed fluctuations.

As the focus of this paper is on mesoscale wind speed fluctuations, the time series has to be filtered before calculating the variance. This is done by a FFT filter. The filter uses the FFT to calculate the amplitudes. As the FFT is designed for periodic time series we mirror the wind speed data. Afterwards, based on the calculated frequency, all amplitudes with a cycle duration longer than 6 h are removed and the time series is reconstructed with an inverse FFT. The result of filtering the wind speed time series is a fluctuation time series, as illustrated in Figure 4(c). The power spectral density of a filtered wind speed time series is shown in Figure 2 in red. It can be seen that the energy of the mesoscale frequencies stays unchanged. This mesoscale fluctuation time series clearly shows the fluctuations of interest at the 8th, 10th and around the 12th of February (Figure 4(c)). At these days, the variance shows the highest values (Figure 4(d)). However, the time series still includes single wind speed ramps with a cycle duration smaller than 6 h. These small wind speed ramps like on the 7th of February results in a smaller variance than recurring wind speed changes due to the used running window calculation (Figure 4(d)).

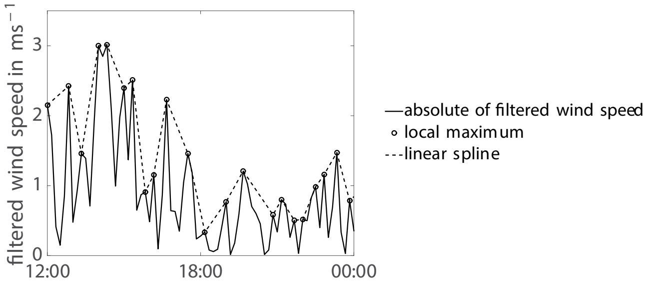

Figure 5: Example for the calculation of the filtered wind speed spline in February 2009.

A related measure for the wind variability in south-eastern Australia is developed by Davy et al. (2010) and for wind power by Ellis et al. (2015) using the standard deviation of a running window applied to a band pass filtered wind speed.

For further comparison, we decide to use the measure based on the 6 h period, because all the periods with mesoscale wind speed fluctuations in the test time series are recognized. And the measure calculated over a 6 h period has high values for recurring wind speed changes only. For each 6 h running window variance period (36 values), the time stamp is set to the 18$^{\text{th}}$ value.

For a real-time calculation, the wind speed measurements of the last recent time steps could be used, considering the sensitivity of the FFT to the used data set length.

The developed fluctuation measure based on FFT and variance can also be applied to spatial fields.

3.3 Filtered wind speed spline

The presented FFT filtered wind speed time series in Figure 4(c) clearly shows higher peaks for the time periods with mesoscale fluctuations. For the development of a fluctuation measure, which remains constantly high for recurring peaks in the filtered wind speed time series, we use a spline through the local maxima.

The procedure is illustrated in Figure 5. The local maxima of the absolute of the filtered wind speed time series are calculated and afterwards connected through a linear interpolation. Therefore, we get a fluctuation measure value for each 10 min time step. The resulting fluctuation measure envelopes the absolute of the fluctuation time series. Figure 6 shows the resulting spline of the filtered wind speed time series.

Like the variance, this fluctuation measure can also be applied to spatial fields or used for the real-time calculation of the fluctuation measure.

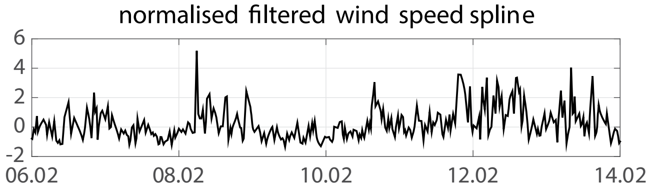

Figure 6: Wind speed spline of the absolute of the filtered wind speed time series in February 2009.

3.4 Increment sum

Wind speed increments are often used for the statistical characterization of short term wind speed fluctuations (e.g. Morales et al., 2012 or Anvari et al., 2016) or for mesoscale wind speeds (Mehrens et al., 2016). We will use a running window increment sum as a mesoscale fluctuation measure.

For the calculation of the increment sum (*inc*), the difference between two consecutive time steps in the wind speed time series is calculated. Because of the focus on recurring wind speed changes, the running window sum of the increments is calculated equivalent to the variance. As for the variance, we use the squared value to get an increased sensitivity of the fluctuation measure at the beginning of recurring wind speed changes. The increment sum (*inc*) for one time period with the length n is calculated as:

$$inc = \sum_{i=1}^{n-1} |x_{i+1} - x_i|^2 \qquad (3.2)$$

The main difference to the calculation of the variance is that we consider the deviation from the last time step and not from the mean of the time period.

Figure 7 compares the results for the increment sum of three time period lengths (n) for the FFT filtered and unfiltered time series. Like for the variance in Section 3.2, the longer the time period, the smoother the fluctuation measure time series. However, contrary to the variance, calculating the increment sum based on either the wind speed or filtered wind speed time series result in similar values. Thus, no filtering of the wind speed is needed.

Another advantage is that the increment sum can be easily calculated for spatial grids and thus for spatial mesoscale fluctuations (Mehrens and von Bremen, 2016).

For further comparison, we use the measure based on the 6 h time period to calculate the running window increment sums of the wind speed time series. The time stamp for the increment sum (36 increments), is set to the 19th value. For real-time calculations, the last 36 values can be used.

3.5 Standardization

For a better comparison of the results, all wind fluctuation measure values are standardized.

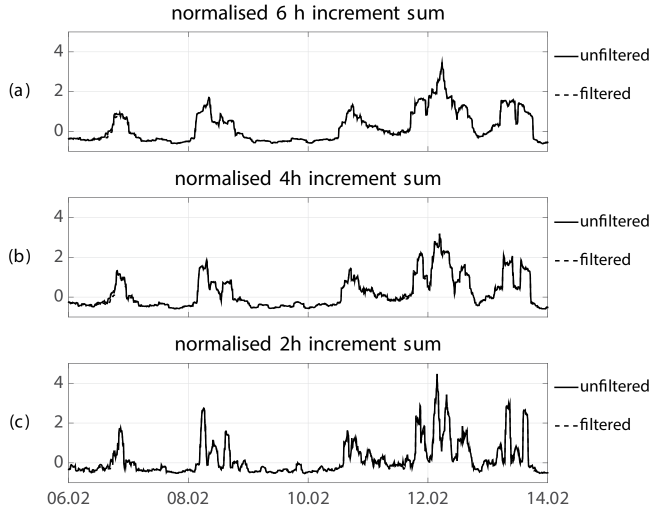

Figure 7: Running window increment sum of the wind speed for different time periods (2 h, 4 h and 6 h in February 2009), using filtered and unfiltered wind speed time series.

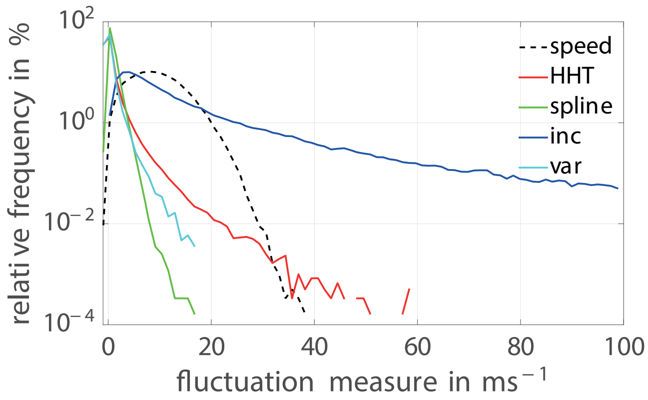

Figure 8: Relative frequency of the individual fluctuation measure values and the wind speed.

Figure 8 shows the relative frequency of the individual fluctuation measure values (y_i). It can be seen that the distribution shapes of the different measures are strongly varying. The individual distribution shapes result from the different methodologies the fluctuation measures are based on. In order to ensure that a comparison of the fluctuation measures only evaluates their sensitivity to mesoscale fluctuations, the slope of the distributions, the most frequent values, and the maximum values should be similar. Different slopes of the distributions, as shown in Figure 8, make the evaluation of the fluctuation measures more complicated, because the measures show different high values during time periods of mesoscale wind speed fluctuations. Thus we standardize the fluctuation measure values by subtracting the mean value ($\overline{y}$) from each fluctuation measure value (y_i) and dividing it by the standard deviation (σ_y) (equation 3.3).

$$z_i = \frac{y_i - \overline{y}}{\sigma_y} \qquad (3.3)$$

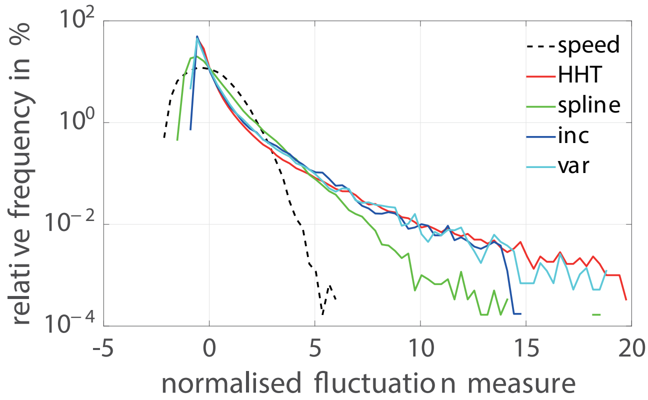

Figure 9: Relative frequency of the individual fluctuation measure values and the wind speed after the standardization (see equation 3.3).

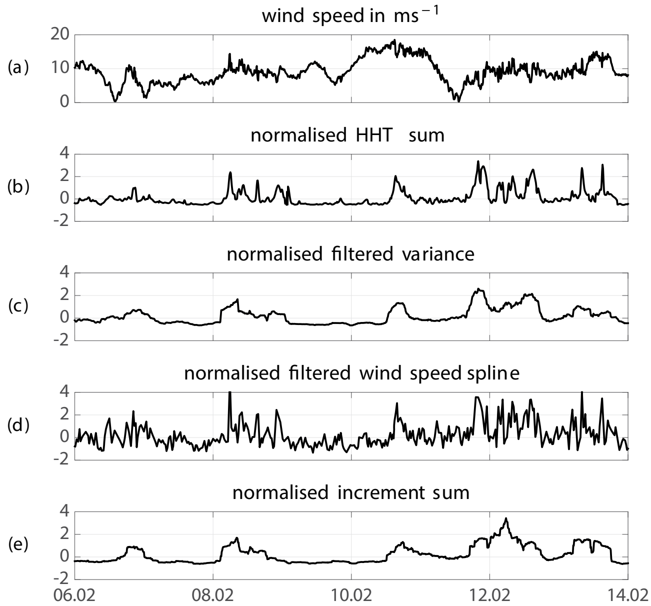

Figure 10: Comparison of all presented mesoscale fluctuation measures in February 2009.

The resulting distributions of the standardized fluctuation measure values (z_i) are shown in Figure 9. The standardization leads to more similar distribution shapes. The maximum values and distribution slopes for the higher fluctuation measure values are still not similar for all measures, but the following sections show that this standardization is sufficient for a comparison. For the following results, all shown fluctuation measure values are standardized.

4 Results

In the following sections, the four presented fluctuation measures will be compared and their sensitivity to mesoscale wind speed fluctuations is tested.

4.1 Intercomparison of the fluctuation measures

Figure 10(b–e) shows all four standardized fluctuation measures for the example period wind speed (Figure 10(a)) in February 2009. It can be seen that all measures identify several time periods with mesoscale fluctuations very similarly. For the 8$^{\text{th}}$, 10$^{\text{th}}$ and 12$^{\text{th}}$ of February we see recurring wind speed changes in Figure 10(a). These time periods are recognized by all measures and have the highest fluctuation measure values. However, due to the very different methodologies, the individual measures react slightly different to the fluctuations in wind speed. The HHT (Figure 10(b)) and the filtered wind speed spline (Figure 10(d)) show a lot of individual peaks. The variance and the increment sum, which are calculated based on a running time period, have more constant high values. Due to the running window calculation, the fluctuation measure reacts already before the fluctuation start.

The example time period includes several wind speed trends with durations longer and shorter than the defined maximum cycle duration of 6 h. The decreasing wind speed trend at the 11$^{\text{th}}$ of February is longer than the time scale we are interested in. Thus, it should not result in a high mesoscale fluctuation measure. This is apparent in all measures. In addition, trends with a time scale shorter than 6 h, like the increasing and decreasing wind speed trends on the 6$^{\text{th}}$ of February result in a moderate fluctuation measure. The measure values are higher for recurring wind speed changes than for ramps.

The comparison of the example data show that in the considered week all fluctuation measures are capable of identifying the wind speed characteristics we are interested in. In the following tests, the measures are tested for the whole FINO 1 wind speed time series (2004–2016).

For a deeper understanding, which fluctuation measures are sensitive to the same phenomena in the wind speed time series and to help to identify if the chosen fluctuation measures are interrelated, Figure 11 shows the bivariate histograms (50 × 50 bins) of all possible fluctuation measure combinations. The relative frequency is calculated for all bins. The bin size is dependent on the minimum and maximum value of the fluctuation measure. Figure 11 demonstrates that all fluctuation measures are related to each other. However, a certain spread is observed. The reason for that are most likely the differing methodologies of the measures which result in a smoothed measure time series due to averaging or a time series with a lot of individual peaks.

More important than the direct comparison of the measures is to test the sensitivity of the fluctuation measures to the wind speed fluctuations we are interested in. In order to decide which measure is most sensitive to situations with mesoscale wind speed fluctuations, the entire wind speed time series is checked visually twice for days with mesoscale wind speed fluctuations. For this purpose the wind speed time series and the filtered

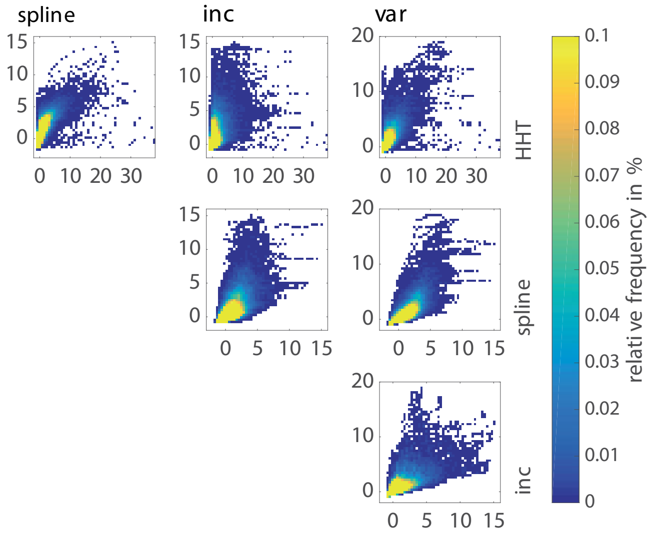

Figure 11: Comparison of all presented mesoscale fluctuation measures in bivariate histograms.

Table 1: Percentile of the mesoscale fluctuation measures to include all manually detected mesoscale fluctuation days.

theoretical	HHT	spline	inc	var
97.97	85.00	86.00	89.00	85.00

wind speed time series are simultaneously checked for time periods of recurring wind speed changes. Only days with obvious mesoscale wind speed fluctuations for the whole day are marked. This procedure is repeated and only days are marked as high fluctuative, which are selected in both selection rounds. These days should also be detected by the fluctuation measure. Not all mesoscale fluctuation phenomena last for a whole day, but because of the length of the time series, daily mean values of the fluctuation measures are used for this comparison. We found 89 highly variable days in the 4384 days long time series. Thus, the highest 2 % percent of the daily fluctuation measure data or days with values above the 98^{th} percentile should include these manually selected days (theoretical value in Table 1). To test this, we calculate stepwise the percentile of the daily mean time series of the fluctuation measures (1.0 steps of the percentile) and check if all manually selected high variable days have higher values than the percentile. Table 1 shows the resulting highest percentiles of the data, when all manually marked days have higher fluctuation measure values than the percentile of the measure and are thus detected by the measure to be fluctuative.

For the increment sum, the percentile closest to the theoretical value is obtained. Nevertheless, the percentiles of the other mesoscale fluctuation measures are very similar. By taking into account that the daily mean of the fluctuation measures is compared with manual decisions, which days are highly variable, all percentiles show good results. Furthermore, most of the mesoscale fluctuation phenomena last less than a day. That makes

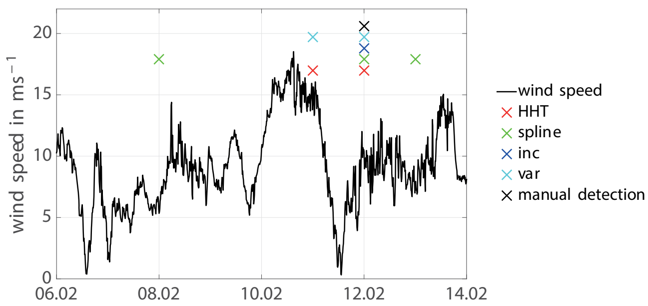

Figure 12: Illustration of the sensitivity test. The black line shows the 10 min wind speed time series and the black crosses mark the days which are manually detected to be highly variable. The colored crosses mark the days which the mesoscale fluctuation measures detect as highly variable based on the percentiles in Table 1.

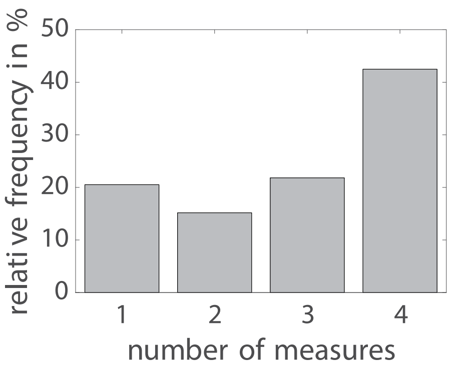

Figure 13: Histogram of how many of the mesoscale wind speed fluctuation measures have at the same days values which are higher than the calculated percentiles.

it difficult to decide manually, if a day is highly variable compared to other days. Figure 12 shows the results for the example week. The colored crosses mark the days which have higher measure values than the percentiles and are thus highly variable. The black crosses show the manually marked day. Figure 13 shows that most often all four fluctuation measures determine the same days as high fluctuative. This leads to the very similar percentile values in Table 1.

Consequently, all measures are capable of identifying days with mesoscale wind speed fluctuations.

4.2 Wind direction dependency

Vincent et al. (2010); Vincent et al. (2011) used conditional Hilbert spectra to show that the most intense mesoscale wind speed fluctuations for the offshore site Horns Rev occur in autumn and winter. The wind variability is increased during situations with precipitation, wind directions from the North Sea, unstable thermal conditions and strong air pressure changes. The strong seasonal cycle of the variability is related to the seasonal cycle in precipitation and surface layer thermal stability. For the calculation of the conditional Hilbert spectrum, the examined variable is binned and an average spectrum is calculated.

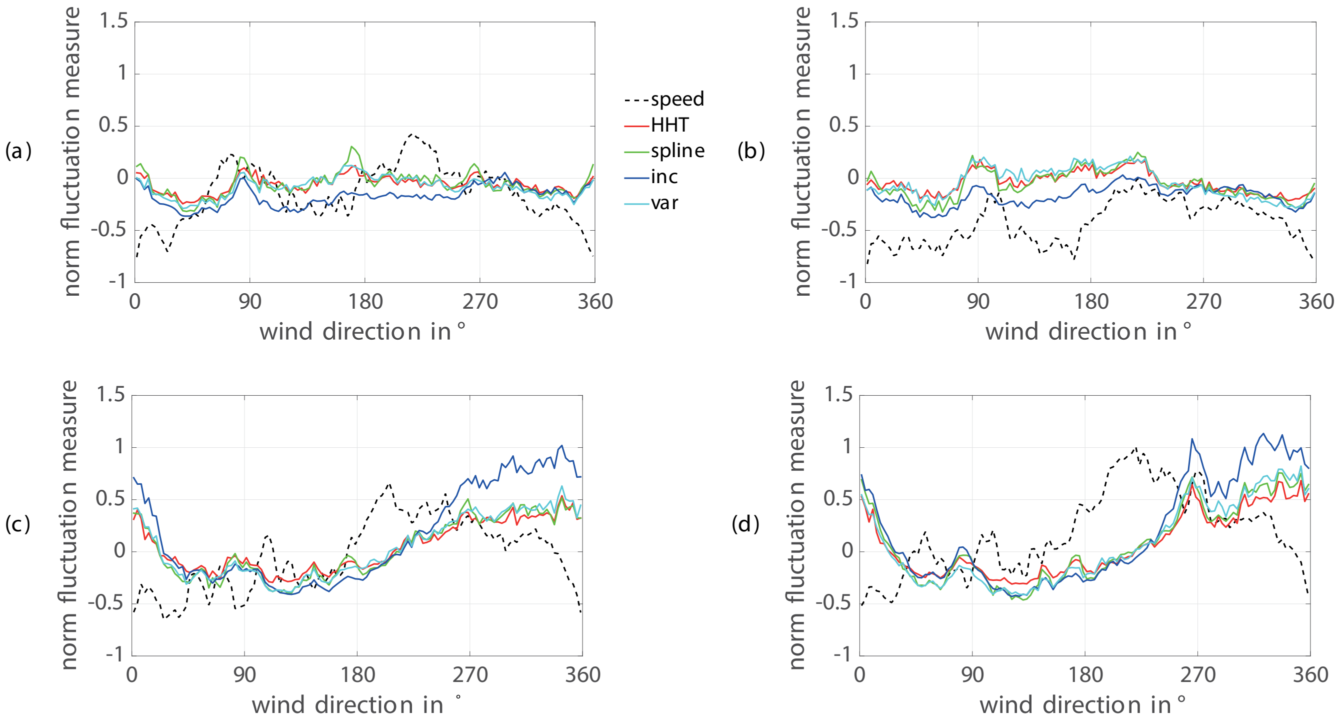

Figure 14: Mean standardized fluctuation measures in dependency on the wind direction (3°bin) for the different seasons spring (a), summer (b), autumn (c) and winter (d) at FINO 1 for the years 2004–2016 in 100 m height.

For the comparison of the four fluctuation measures, we repeat this procedure for the seasonal wind direction dependency of the FINO 1 wind speed measurements. For the comparison of the different mean fluctuation measures we use a wind direction bin of 3°. The influence of the lightning cage on the wind speed measurements and the mast shadow on the wind direction measurement is not corrected and thus visible in the resulting conditional fluctuation measure mean values.

Figure 14 shows the impact of the wind direction on the wind speed variability for all meteorological seasons. The standard error of the fluctuation measure mean value is very small due to the sample size and thus not shown here.

Even though the standardization of the fluctuation measures did not result in equally shaped distributions (Figure 9) and in regard to the very small wind direction bin size, the mean fluctuation measures are quite similar. The same standardization is used for the wind speed. In accordance with Vincent et al. (2011), the variability measures are higher in autumn and winter for flow from the open North Sea (∼ 240° – 30°). Vincent (2010) explains this higher wind variability with mesoscale convection which evolves during cold air outbreaks.

The comparison with the mean wind speed shows that the wind direction with the highest variability in autumn and winter (∼ 270° – 20°) is not corresponding to the wind direction with the highest wind speeds (∼ 180° – 300°).

These results show that all variability measures yield to the same results although being quite different with regard to their calculation method and complexity.

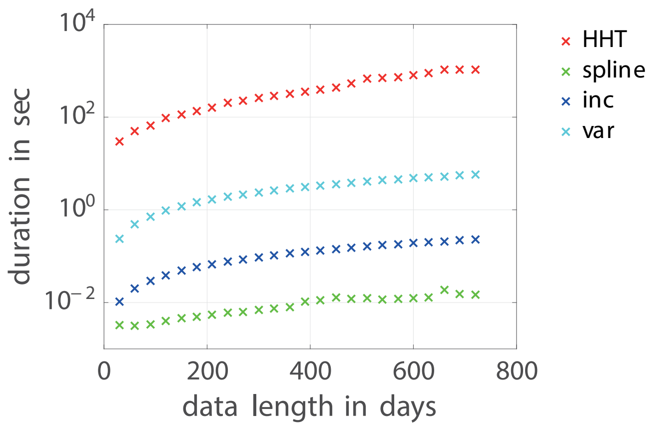

Figure 15: Comparison of the computation time of all presented mesoscale fluctuation measures in dependency on the length of the time series. For the calculations a desktop computer (Core i3 CPU at 3.40 GHz × 2) and Matlab is used.

4.3 Computation time

The different complexity of the calculation of the fluctuation measures can be illustrated by the computation time. Figure 15 shows the computation time as a function of the data set length. For the calculation a desktop computer and the same example data sets are used. The resulting computation times vary strongly. The shortest computation time is achieved for the filtered wind speed spline. The longest computation time is needed for the HHT fluctuation measure. The long computation time of this fluctuation measure is a disadvantage for analyzing long time series. Particularly, if several time series of different sites are compared. The mesoscale fluctuation measures can also be used to calculate spatial variations on a grid. The short computation time is an advantage when a high number of grid points is investigated or for the real-time calculation of the measures.

5 Conclusions

We compared four different empirical methods to measure mesoscale wind speed fluctuations: the first is a measure based on the Hilbert-Huang Transform, the second a running variance of a Fast-Fourier Transform filtered wind speed time series, the third calculates a spline around the Fast-Fourier filtered wind speed time series and the fourth uses the running increment sum of the wind speed time series.

The method complexity and thus computation times are very unequal. Nevertheless, all fluctuation measures are capable of identifying days with high mesoscale wind speed fluctuations. Also, the wind direction dependency shows comparable characteristics for all four seasons. All methods, except the HHT due to the end effect, could also be used to calculate the real-time mesoscale wind speed fluctuations based on past measurements.

From our perspective, the most favorable measure is the increment sum, because no transformation is necessary and the implementation is thus very easy and the computation time very short. Furthermore, it can easily be used for spatial grids.

The presented methods for measuring mesoscale wind speed fluctuations could be used in the future to determine the driving force behind mesoscale wind speed fluctuations. Some highly variable situations only last for hours and some for several days, which indicates different phenomena causing the fluctuations. The manual examination of the long wind speed and fluctuation measure time series showed that some years have more days with mesoscale wind speed fluctuations than others and thus a one year time series seems not enough to capture all phenomena which cause fluctuations. A detailed study of the phenomena and their driving forces would enable the development of a statistical day-ahead forecast, which could be based on numerical weather predictions.

Future work could also focus on patterns of wind speed changes which indicate a periodic triggering of the phenomena and can be used to identify fluctuations with pattern recognition.

Acknowledgments

The work presented in this study is funded by the Ministry of Science and Culture of Lower Saxony within the PhD Program "System Integration of Renewable Energies" (SEE) and the project ventus efficiens (ZN3024, MWK Hannover). The authors acknowledge the Federal Maritime And Hydrographic Agency (BSH) for providing FINO 1 wind speed and direction data.

References

Anvari, M., G. Lohmann, M. Wächter, P. Milan, E. Lorenz, D. Heinemann, M.R. Rahimi Tabar, J. Peinke, 2016: Short term fluctuations of wind and solar power systems. – New J. Phys. **18**, 063027, DOI: 10.1088/1367-2630/18/6/063027.

Barthlott, C., P. Drobinski, C. Fesquet, T. Dubos, C. Pietras, 2007: Long-term study of coherent structures in the atmospheric surface layer. – Bound.-Layer Meteor. **125**, 1–24, DOI: 10.1007/s10546-007-9190-9.

Davy, R.J., M.J. Woods, C.J. Russell, P.A. Coppin, 2010: Statistical downscaling of wind variability from meteorological fields. – Bound.-Layer Meteor. **135**, 161–175, DOI: 10.1007/s10546-009-9462-7.

Duffy, D.G., 2004: The application of Hilbert-Huang Transforms to meteorological datasets. – J. Atmos. Oceanic Technol. **21**, 599–611, DOI: 10.1175/1520-0426(2004)021<0599:TAOHTT>2.0.CO;2.

Ellis, N., R. Davy, A. Troccoli, 2015: Predicting wind power variability events using different statistical methods driven by regional atmospheric model output. – Wind Energy **18**, 1611–1628, DOI: 10.1002/we.1779 WE-13-0287.R1.

Foley, A.M., P.G. Leahy, A. Marvuglia, E.J. McKeogh, 2012: Current methods and advances in forecasting of wind power generation. – Renewable Energy **37**, 1–8, DOI: 10.1016/j.renene.2011.05.033.

Georgilakis, P.S., 2008: Technical challenges associated with the integration of wind power into power systems. – Renewable and Sustainable Energy Reviews **12**, 852–863, DOI: 10.1016/j.rser.2006.10.007.

Ghil, M., M.R. Allen, M.D. Dettinger, K. Ide, D. Kondrashov, M.E. Mann, A.W. Robertson, A. Saunders, Y. Tian, F. Varadi, P. Yiou, 2002: Advanced spectral methods for climatic time series. – Reviews of Geophysics **40**, 3–1–3–41, DOI: 10.1029/2000RG000092.

Huang, N.E., Z. Wu, 2008: A review on Hilbert-Huang transform: Method and its applications to geophysical studies. – Rev. Geophys. **46**, published online, DOI: 10.1029/2007RG000228.

Huang, N.E., Z. Shen, S.R. Long, M.C. Wu, H.H. Shih, Q. Zheng, N.-C. Yen, C.C. Tung, H.H. Liu, 1998: The empirical mode decomposition and the hilbert spectrum for nonlinear and non-stationary time series analysis. – Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences **454**, 903–995, DOI: 10.1098/rspa.1998.0193.

Larsén, X.G., C.L. Vincent, S.E. Larsen, 2013: Spectral structure of mesoscale winds over the water. – Quart. J. Roy. Meteor. Soc. **139**, 685–700, DOI: 10.1002/qj.2003.

Mehrens, A.R., L. von Bremen, 2016: On the correlation of spatial wind speed and solar irradiance variability above the north sea. – Adv. Sci. Res. **13**, 57–61, DOI: 10.5194/asr-13-57-2016.

Mehrens, A.R., A.N. Hahmann, X.G. Larésn, L. von Bremen, 2016: Correlation and coherence of mesoscale wind speeds over the sea. – Quart. J. Roy. Meteor. Soc. **142**, 3186–3194, DOI: 10.1002/qj.2900.

Morales, A., M. Wächter, J. Peinke, 2012: Characterization of wind turbulence by higher-order statistics. – Wind Energy **15**, 391–406, DOI: 10.1002/we.478.

Orlanski, I., 1975: A rational subdivision of scales for atmospheric processes. – Bull. Amer. Meteor. Soc. **56**, 527–530.

RCADA, 2015: HHT MATLAB program runcode package. – http://rcada.ncu.edu.tw/research1_clip_program.htm, last accessed September 18, 2015, Research Center for Adaptive Data Analysis, National, Central University, Taiwan.

Strang, G., 1989: Wavelets and dilation equations: A brief introduction. – SIAM Review **31**, 614–627, DOI: 10.1137/1031128.

Tande, J.O.G., 2003: Grid integration of wind farms. – Wind Energy **6**, 281–295, DOI: 10.1002/we.91.

Vincent, C., 2010: Mesoscale wind fluctuations over Danish waters. – Ph.D. thesis, Technical University of Denmark. Risø National Laboratory for Sustainable Energy.

Vincent, C., G. Giebel, P. Pinson, H. Madsen, 2010: Resolving nonstationary spectral information in wind speed time series using the Hilbert-Huang transform. – J. Appl. Meteor. Climatol. **49**, 253–267, DOI: 10.1175/2009jamc2058.1.

Vincent, C.L., P. Pinson, G. Giebel, 2011: Wind fluctuations over the North Sea. – Int. J. Climatol. **31**, 1584–1595, DOI: 10.1002/joc.2175.

Wu, Z., N.E. Huang, 2004: A study of the characteristics of white noise using the empirical mode decomposition method. – Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences **460**, 1597–1611, DOI: 10.1098/rspa.2003.1221.

Wu, Z., N.E. Huang, 2009: Ensemble empirical mode decomposition: A noise-assisted data analysis method. – Adv. Adaptive Data Analysis **01**, 1–41, DOI: 10.1142/S1793536909000047.