The effect of microphone wind noise on the amplitude modulation of wind turbine noise and its mitigation

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Abstract: Microphone wind noise can corrupt outdoor recordings even when wind shields are used. When monitoring wind turbine noise, microphone wind noise is almost inevitable because measurements cannot be made in still conditions. The effect of microphone wind noise on two amplitude modulation (AM) metrics is quantified in a simulation, showing that even at low wind speeds of 2.5 m/s errors of over 4 dBA can result. As microphone wind noise is intermittent, a wind noise detection algorithm is used to automatically find uncorrupted sections of the recording, and so recover the true AM metrics to within ±2/±0.5 dBA.

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1. Introduction

Microphone wind noise is known to corrupt many outdoor measurements. In particular, measurements of amplitude modulation (AM) from wind turbines are biased by microphone wind noise. Mitigation usually takes the form of applying wind shields. But when the signal level is low and wind speed near the ground is high, even very efficient wind shields may not be sufficient.

The IoA Good Practice guide to the application of ETSU-R-97 (IoA, 2013) suggests that noise levels from wind turbines external to a dwelling should be limited to 43 dBA (LA90) when background noise levels are low. This upper limit is in line with international regulations (von Hünerbein *et al.*, 2013b). Lower limits of typically 35 dBA (LAeq) at nighttime are also common. When background noise is high the recommended limit is 5 dBA above the background level. The level of noise induced by the wind at a microphone varies with conditions and wind shield but van den Berg (2006) suggests that a microphone with a 10 cm shield in 5 ms^{-1} wind induces approximately 40 dBA wind noise. Therefore even at moderate wind speeds, the magnitudes of wind turbine and microphone wind noise are of a similar order and as turbines only produce noise when wind is present, it is of particular importance to quantify this bias error. For most modern large scale wind turbines the dominant AM occurs between 0.5 and 2 Hz (von Hünerbein *et al.*, 2013a). When the wind is relatively constant, the microphone wind noise will act to reduce the amplitude of modulations, but when gusting is present additional modulation energy in the 0.5–2 Hz region will be introduced.

Three AM metrics have recently been proposed by the Institute of Acoustics and so far mainly evaluated from wind turbine recordings which were manually filtered for sound quality (Bass *et al.*, 2015). In this work a simulation is carried out combining turbine noise with microphone wind noise at various wind speeds, two AM metrics are calculated, and the resulting bias error quantified. Subsequently, a wind noise detection algorithm operating on just the audio signal is used to indicate regions of audio containing wind noise. These sections are removed from the calculation of the AM metric and the improvement in accuracy evaluated.

2. AM metrics

Of the three proposed AM metrics one is based on a time series analysis, one on a frequency analysis, and a third that combines the two.

In accordance with Fukushima *et al.* (2013), evaluating Metric 1 begins by calculating the time varying difference (ΔL) between the A-weighted sound pressure

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level measured using the standard fast and slow integration periods found on sound level meters. The metric is then the difference between the 5th and 95th percentile values of ΔL. This aims to de-trend the sound pressure level time series or in other words to remove any drift in the data (Bass *et al.*, 2015).

Metric 2 relies on a frequency domain analysis. First, the measured sound pressure is A-weighted and bandpass filtered to a frequency range relevant to the modulation. In the current paper 150–400 Hz is used. Frequency domain analysis (fast Fourier transform) is performed on the resulting envelope with a high temporal resolution such as 100 ms (Bass *et al.*, 2015). Peaks in the low frequency envelope spectrum are used to quantify the AM.

3. Simulating errors caused by microphone wind noise in AM metrics

To understand the magnitude of the errors in AM metrics caused by microphone wind noise a simulation is carried out. Synthesized examples of wind turbine noise with varying levels of AM from von Hünerbein *et al.* (2013a) are used to systematically investigate the influence of microphone wind noise at known modulation levels. Originally used for a subjective response study, 5 sound samples of 20 s duration with nominal modulation depths of 0, 3, 6, 9, and 12 dBA are selected for the simulation. These samples were originally produced in MATLAB and auralized using an ambisonic sound system in a Listening Room. The sounds used here are recordings of the auralized samples captured from a single low-noise microphone. Using synthesized wind turbine samples guarantees that microphone wind noise is not present, the captured auralized audio was recorded as there was no access to the fully synthesized mono stimuli, and these recordings are known in the community (Bass *et al.*, 2015).

In a second step, synthesized microphone wind noise was added to the AM samples. The microphone wind noise was generated using a simulator implemented by Jackson *et al.* (2014). The simulation uses measured sonic anemometer wind time histories available from the CASES-99 database (Fritts *et al.*, 2001) to generate audio based on the model by van den Berg (2006). van den Berg showed that the sound pressure level Lp for the one-third octave centered at frequency f, for a shielded microphone, can be approximated by

$$L_p(f) = 40\log_{10}(V) - 6.67\log_{10}(fD/V) - 10\log_{10}(1 + (3fD/V)^2) + 42, \tag{1}$$

where V is wind speed and D is wind screen diameter. A 10 cm wind shield is chosen. The one-third octave sound pressure level is converted to an amplitude spectrum with a linear frequency scale by linear interpolation. Subsequently, a time history of pressure values is generated by assigning a random phase to each bin in the resulting amplitude spectrum and applying an inverse Fourier transform. Time varying microphone wind noise is generated by utilizing wind velocity time histories taken from anemometer data. The sonic anemometer data with a time resolution of 100 ms are linearly interpolated to increase the resolution to 50 ms, and for each resulting wind velocity data point, a 100 ms window of noise generated. A Hanning window is applied to each of the noise windows, and then a 50% overlap and add scheme used to create a 20 s audio sample of time varying microphone wind noise. This enables wind noise samples to be generated with arbitrary wind speed time histories representing a wide range of wind conditions recorded over 8 days from 8 sonic anemometers on 5 towers, 3 at a height of 5 m and 5 at a height of 2 m. Further details on the simulation methodology are available in Jackson *et al.* (2014).

Wind turbine test signals corrupted with microphone wind noise were generated using 35 target mean wind speeds from 1.5 to 10 m/s in 0.25 m/s steps. For each target wind speed five examples were generated by repeated random selection from the available data. The playback level of the test file in the RenewableUK study (von Hünerbein *et al.*, 2013a) was 40 dBA. The microphone wind noise simulator produces a pressure time history in Pascals, and therefore it is straightforward to combine the wind turbine and microphone wind noise so that the relative levels are representative of real conditions.

The two AM metrics are computed for all examples, and the error in the metric as a function of wind speed is calculated. The error is quantified as the difference between the metrics with and without microphone wind noise. For each metric and target wind speed, the mean and standard error was computed from the five instances of that wind speed.

Figure 1 shows that for the time series metric, as the wind speed increases the error in the modulation depth also increases. When there is little AM in the wind turbine signal, microphone wind noise will tend to increase the modulation depth. But

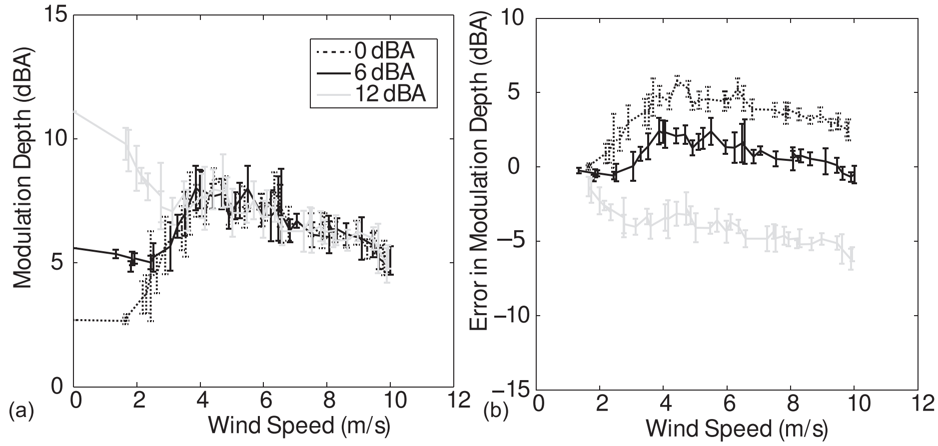

Fig. 1. Metric 1 average rating as a function of wind speed: (a) absolute AM rating and (b) error due to microphone wind noise. The AMs were designed to be 0 dBA (dashed line), 6 dBA (black line), and 12 dBA (gray line). Error bars represent 95% confidence limits.

when there are high modulation depths in still conditions, the addition of wind noise reduces the metric. This is because the wind noise can often contain gusts which will act to increase the modulation depth when the background level is stationary, but when very strong modulations already exist, the modulations will be masked by the wind noise. The simulations show that errors can occur even at very low wind speeds. Errors exceed 2 dBA from 2 m/s.

Figure 2 shows the same data but using the frequency domain metric. This shows that the metric is more robust at low wind speeds below around 3.5 ms^{-1} although above this both methods exhibit strong bias errors. This increase in robustness when compared to the time domain metric, is due to the band limiting to 150–400 Hz, as microphone wind noise is dominated by low frequencies.

4. Automatic detection of wind noise to reduce metric errors

A microphone wind noise detection algorithm was developed by Jackson *et al.* (2014). The algorithm is a machine learning algorithm where an ensemble of decision trees has been trained to classify short, 23 ms frames of audio according to the level of wind noise present. The training database was generated from both real and simulated examples of microphone wind noise combined with many examples of foreground and background sounds. The wind noise level of every audio frame is identified according to the following bands:

(a) $\mathrm{ClassL} = 0 : \mathrm{LAeq} < 30\,\mathrm{dBA}$,
(b) $\mathrm{ClassL} = 1 :\ 30 < \mathrm{LAeq} <= 50\,\mathrm{dBA}$,
(c) $\mathrm{ClassL} = 2 :\ 50 < \mathrm{LAeq} <= 70\,\mathrm{dBA}$,
(d) $\mathrm{ClassL} = 3 :\ \mathrm{LAeq} > 70\,\mathrm{dBA}$.

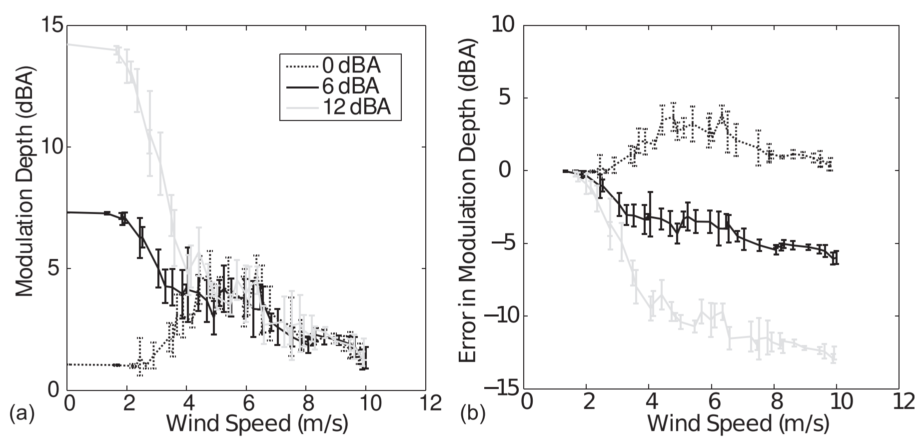

Fig. 2. Metric 2 average rating as a function of wind speed: (a) absolute AM rating and (b) error due to microphone wind noise. The AMs were designed to be 0 dBA (dashed line), 6 dBA (black line), and 12 dBA (gray line). Error bars represent 95% confidence limits.

ClassL is then averaged over 1 s, forming one of two main outputs of the wind noise detection algorithm the resulting class average linearly correlates with the LAeq between 30 and 70 dBA. To identify microphone wind noise a simple threshold is applied on the average wind noise level class of 0.5. An average class of 0.5 indicates 50% of time the level is less than 30 dBA and 50% of time it is between 30 and 50 dBA. While there is not a one to one functional mapping between average class and level, this was found to correspond to an A-weighted level of around 30 dBA. This is 10 dBA below the level of the wind turbine noise and chosen as an appropriate threshold to classify regions as wind noise free. Jackson *et al.* (2014) reported that the Mathews Correlation Coefficient, which is a balanced measure of binary classification performance, was around 0.6 when wind noise was combined with other sounds. The wind noise detection algorithm is applied to all examples from Sec. 3. For each of the five modulation depths, the average AM metrics are computed (1) over the whole data set including segments corrupted with wind noise examples, and (2) only using time segments where the estimated average wind noise level class is below 0.5. Figure 3 compares the error in the AM metrics with and without data rejection based on the wind noise detection. For both metrics the accuracy is significantly improved by rejecting data with microphone wind noise.

5. Discussion

The IoA discussion document (Bass *et al.*, 2015) indicates that there is an expectation of a low influence from wind noise on the AM rating where band limited frequency domain rating methods are used. This is in stark contrast to the results presented in Fig. 2, where even at relatively low wind speeds there remains acoustic energy from the wind noise in the frequency band of interest. Very similar results have been produced for both the band limit 100–400 Hz proposed by Bass *et al.* (2015) and for the presented 150–400 Hz.

It should be noted that the study used the windshield which is recommended by the IoA Good Practice guide (IoA, 2013), as the minimum acceptable shield specification. The accuracy of the AM metrics is therefore expected to be better where enhanced-performance windshields are used. Figure 3 shows that rejection of samples which have been identified to contain wind noise, reduces the error in the AM metric to less than 2 and 0.5 dBA for Metrics 1 and 2, respectively. The performance needs to be tested with real recordings containing other ambient noises such as bird song and traffic noise, as these will be likely to affect the ratings. Restriction of data availability in high wind noise conditions needs also to be assessed as excessive filtering of data in high wind conditions can lead to a data availability bias, e.g., high AMs might occur at high wind speeds but they are not included because considerable periods might be rejected. In practice, this might not be a significant limitation of the method as it has been reported that AM from wind turbines is particularly disruptive in wind shear conditions (van den Berg, 2004). In those situations the wind speeds at microphone level near the ground are lower than at wind turbine hub height and excessive wind noise on the microphone is not expected. Following this it would also be useful to measure high resolution such as 10 s wind speeds at the microphone locations to improve AM rating quality assessment.

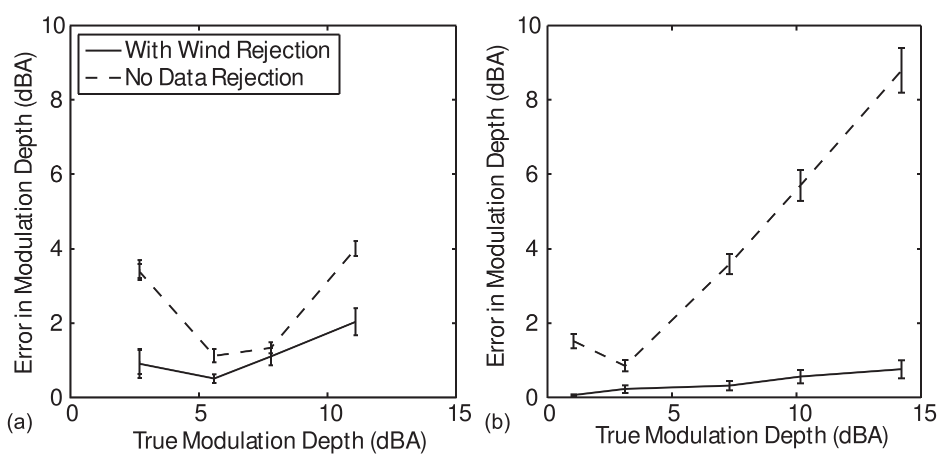

Fig. 3. AM metric accuracy with and without wind noise rejection: (a) Metric 1 and (b) Metric 2.

6. Conclusions

The study evaluates the robustness of the proposed IoA metrics (Bass *et al.*, 2015) in the frequency domain and the time domain (Metrics 1 and 2) under the influence of simulated microphone wind noise using a 10 cm diameter wind shield. Crucially, both metrics show large errors in the AM metric from wind speeds as small as 3 m/s. This suggests that using these metrics where considerable microphone wind noise is present will underestimate large turbine noise modulation depths and overestimate small turbine noise modulation depths.

Automated microphone wind noise detection has been shown to considerably improve the ratings. This is because, provided that the microphone wind noise level fluctuates more quickly than the AM metrics, there are periods where the metrics will be reliable. Simulations indicate that detection of these periods has been successful, but further experiments are needed to confirm this in realistic scenarios. In the meantime the use of an automatic weather station with a sufficiently high time resolution might be the only way to inspire some confidence in the proposed AM ratings. The wind noise detector is available as an open source C++ program (Kendrick *et al.*, 2014).

Acknowledgments

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