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Detection of Amplitude Modulation in Southern Ontario Wind Farms

Duncan Halstead, Adam Suban-Loewen, Payam Ashtiani
Aercoustics Engineering 50 Ronson Drive, Toronto M9W 1B3
E-mail: duncanh@aercoustics.com
E-mail: adams@aercoustics.com
E-mail: payama@aercoustics.com

SUMMARY

This paper details the results of an automated detection algorithm based on the method developed for the RenewableUK study on Amplitude Modulation (AM) in wind turbines. The algorithm was used to evaluate the possible presence of AM in five different wind farms of varying size and turbine model in Southern Ontario, Canada. Measurement locations were at nearby residences, roughly 500m to 800m from the nearest turbines. The data available for analysis represents over 7000 hours of sound recordings, acquired between the months of March and December 2014.

The ability of the algorithm to successfully detect AM was verified by listening to the recordings where the algorithm detected AM. The algorithm was found to be generally successful in detecting amplitude modulation, and with a few adjustments, was able to filter out the influence of ambient amplitude modulations from insects and small fauna. The algorithm, however, is still susceptible to amplitude modulation from ambient sources that modulate at mid frequencies.

The analysis also found that while wind turbine AM was readily detectable, the rate of occurrence of AM at a particular measurement location was, at maximum, less than 0.25% of the total measurement time.

1 INTRODUCTION

Wind turbine noise Amplitude Modulation (AM) has been the subject of a detailed study by RenewableUK [1]. As part of that study, a method was developed by Cand and Bullmore to detect the presence of AM in a sound recording [2]. This paper presents the results of this method, with some modifications, applied to a very large dataset of sound recordings measured at various wind farms across Southern Ontario, Canada. The wind farms range in size from less than 5 turbines to over 100. The turbines comprise many different manufacturers, but are all considered to be large industrial turbines, with power ratings over 1.5 MW and rated rotational speeds between 14 and 15 rpm.

This paper evaluates the ability of the modified algorithm to detect AM, as well as evaluate the rate of occurrence of AM. Results were qualitatively verified by listening to the sound recording in the regions where turbine-attributed AM was detected. The overall rate of occurrence of turbine AM was also evaluated by calculating the probability density function of the modulation depths measured near the turbine blade-pass frequency (BPF).

2 MEASUREMENT SETUP AND SITE CONDITIONS

Sound recordings were measured using a B&K 4189 microphone, ZC-0032 pre-amplifier, and 2250 sound level meter. The sound level meter was programmed to store 24-bit sound recordings with an 8kHz sampling frequency. Recordings were taken between 10pm and 5am every night. The microphone was fitted with a primary and secondary windscreen to reduce the effect of wind generated self-noise. A picture of the measurement apparatus is shown in Figure 1.

The measurement rigs were located at a variety of locations spread across five wind farms in Southern Ontario. The size of each wind farm ranged from just under 5 turbines to over 100 and each wind farm comprised different makes and models of wind turbine. The turbines measured were all modern industrial turbines, with blade diameters and hub heights greater than 90m. The areas surrounding the measurement locations were primarily open fields with intermittent shelter belts, as is common for Southern Ontario. Measurement rigs were located between 500m and 800m from the nearest turbines.

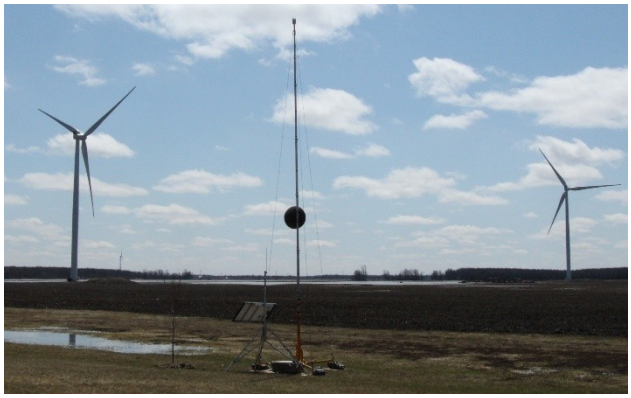

Figure 1: Measurement apparatus

All of the measurements used for analysis in this paper were taken between March and December 2014. Each measurement campaign was between 3 weeks and 2 months.

All measurements were unattended, therefore it was necessary to develop an algorithm capable of sifting through large amounts of data automatically.

3 METHODOLOGY

The algorithm used to detect AM is based on the algorithm developed by Cand and Bullmore for the RenewableUK study done in December 2013 [2].

The algorithm begins by calculating the A-weighted equivalent sound pressure level (LA_{eq}) in 100ms intervals for the entire measurement duration. This calculation is done on both the raw sound recording, and later on the same input data bandpassed from 200Hz to 1kHz. An example of the level vs. time of a signal containing AM is shown in Figure 2.

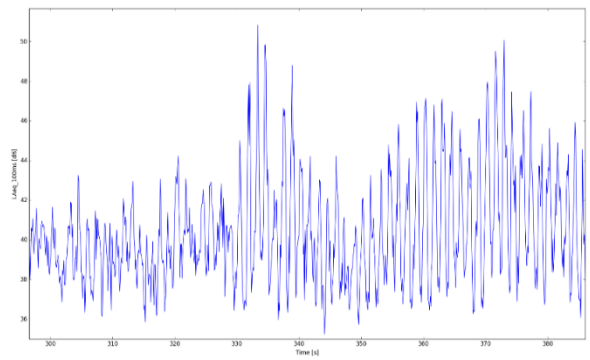

Figure 2: A-weighted level vs. time of a signal containing wind turbine AM starting 1/3rd the way through the recording.

The A-weighted LA_{eq} vs. Time is divided into 10 second segments, excluding intervals where the overall LA_{eq} is greater than 60 dBA or when the maximum level is greater than 10dB above the mean. Each 10 second segment is then detrended by subtracting a 5-th order polynomial fit.

The algorithm uses a Fast Fourier Transform (FFT) to calculate the Power Spectral Density (PSD) of each 10 second LA_{eq} vs. Time segment. The PSDs are then converted back to a scaled peak-peak amplitude spectrum using the following equation:

$$Amplitude\ Spectra_{p-p} = 2\sqrt{2 * frequency\ resolution * PSD}$$

The resulting peak-peak amplitude spectra are integrated with a frequency window of width 20% of the turbine BPF. The reason for integrating the signal is to reduce the dependency of the FFT on the windowing function as well as match the amplitudes of the FFT with the amplitudes in the LA_{eq} vs. Time. The integration also helps smooth the curves in the FFT which reduces the number of small spectral peaks associated with random noise. The peaks of the integrated peak-peak amplitude spectra in the neighbourhood of the BPF are taken as an estimation of the wind turbine AM depth for a 10 second segment.

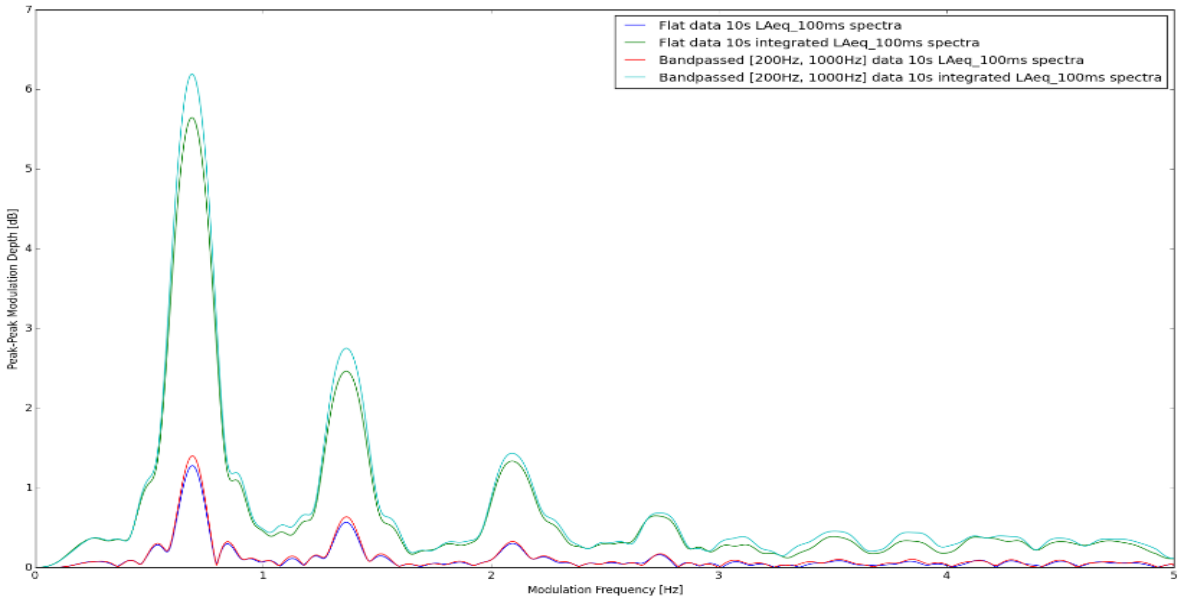

Figure 3: Modulation Frequency Spectrum of 10 second A-weighted LAeq vs. time interval. The first peak represents the wind turbine BPF

To aggregate the results of the algorithm applied to thousands of hours' worth of data, modulation spectrograms were created for each measurement campaign. These spectrograms show the modulation depth as a function of time and frequency, over the course of an entire measurement. Note that points are plotted in order, starting with smallest modulation depth and ending with largest modulation depth, thus emphasizing the largest modulation depths to facilitate detection of AM.

Modulation depths between -20% of BPF to + 10% of BPF were collected for an entire measurement and used to generate a probability density function. The probability density is used to estimate the rate of occurrence of AM at significant modulation depths.

4 PRELIMINARY RESULTS

4.1 Detection of Amplitude Modulation

The results of the detection algorithm are presented for a few cases below. The data is plotted as a modulation spectrogram with time on the x-axis, modulation frequency on the y-axis, and modulation depth as the colour; higher modulations have "warmer" colours. Modulations around the BPF can be seen in all three figures below.

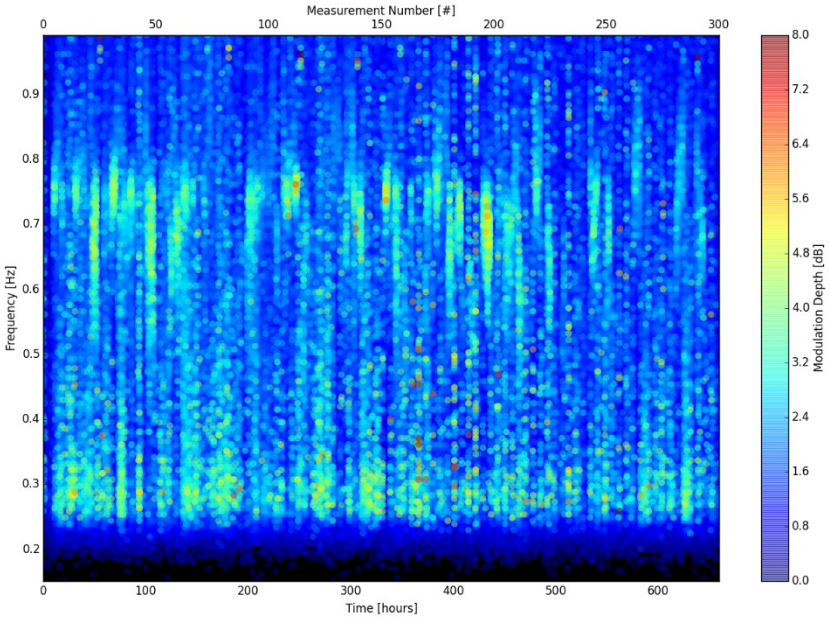

Figure 4: Modulation spectrogram showing modulation around the BPF of the turbine. This measurement location was 580m from the nearest turbine

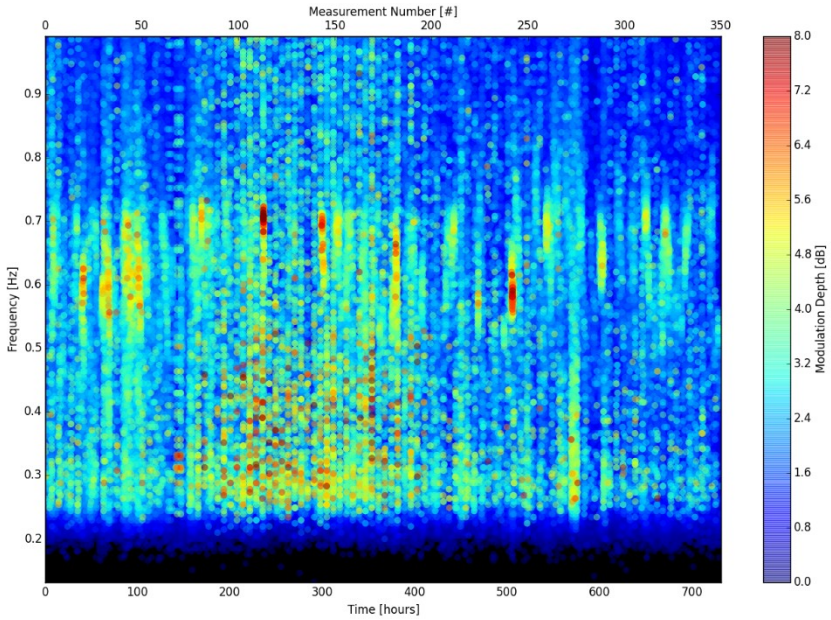

Figure 5: Modulation spectrogram showing modulation with high contamination from other sources. This measurement location was 725m from nearest turbine

Figure 4 shows a relatively clean modulation signal from the wind turbine BPF, with modulation depths of up to 5dB apparent. Listening to the sound recording of the

measurement confirmed that the distinctive swish attributed to a wind turbine was audible during the times where AM was detected by the algorithm.

Figure 5 shows a spectrogram that has a similar trend of higher modulation around the wind turbine BPF, however, it is heavily contaminated with other modulations not expected to be associated with a wind turbine. Listening to the sound recording revealed a significant amount of audible AM.

Figure 6 shows frequency of modulation vs. time of a large wind farm. In this dataset, modulations at the wind turbine BPF are present in only a few isolated cases.

One notable feature of these plots is that there is a great deal of modulation detected that is outside the expected frequencies for a wind turbine, particularly around 0.3Hz but also at other random frequencies (see **Error! Reference source not found.**). These modulations could be caused by the wind, car passes, animals, insects and any other source that modulates with time. To reduce the effect of these extraneous modulations, a bandpass filter was applied to the raw data, excluding data below 200Hz and above 1000Hz.

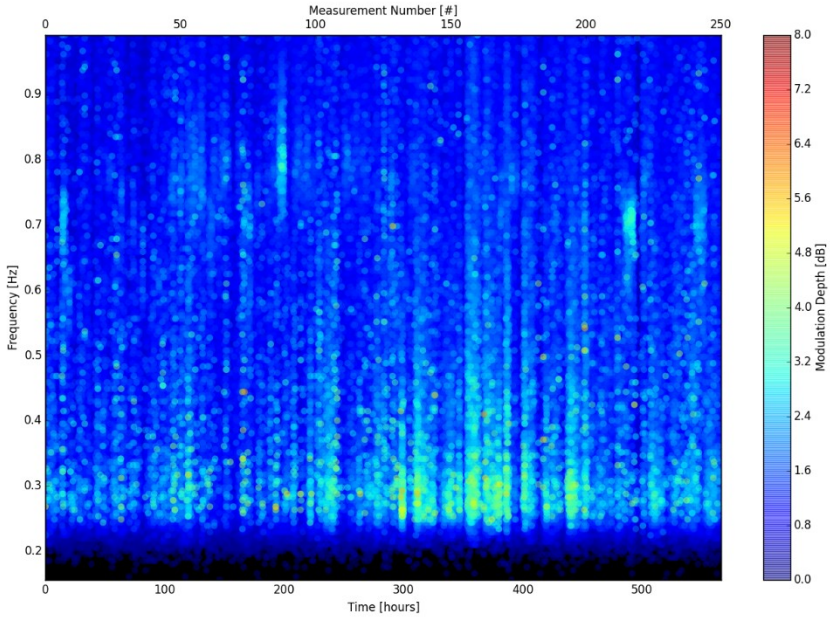

Figure 6: Modulation spectrogram showing modulation in isolated intervals at the BPF. This measurement location was 660m from nearest turbine

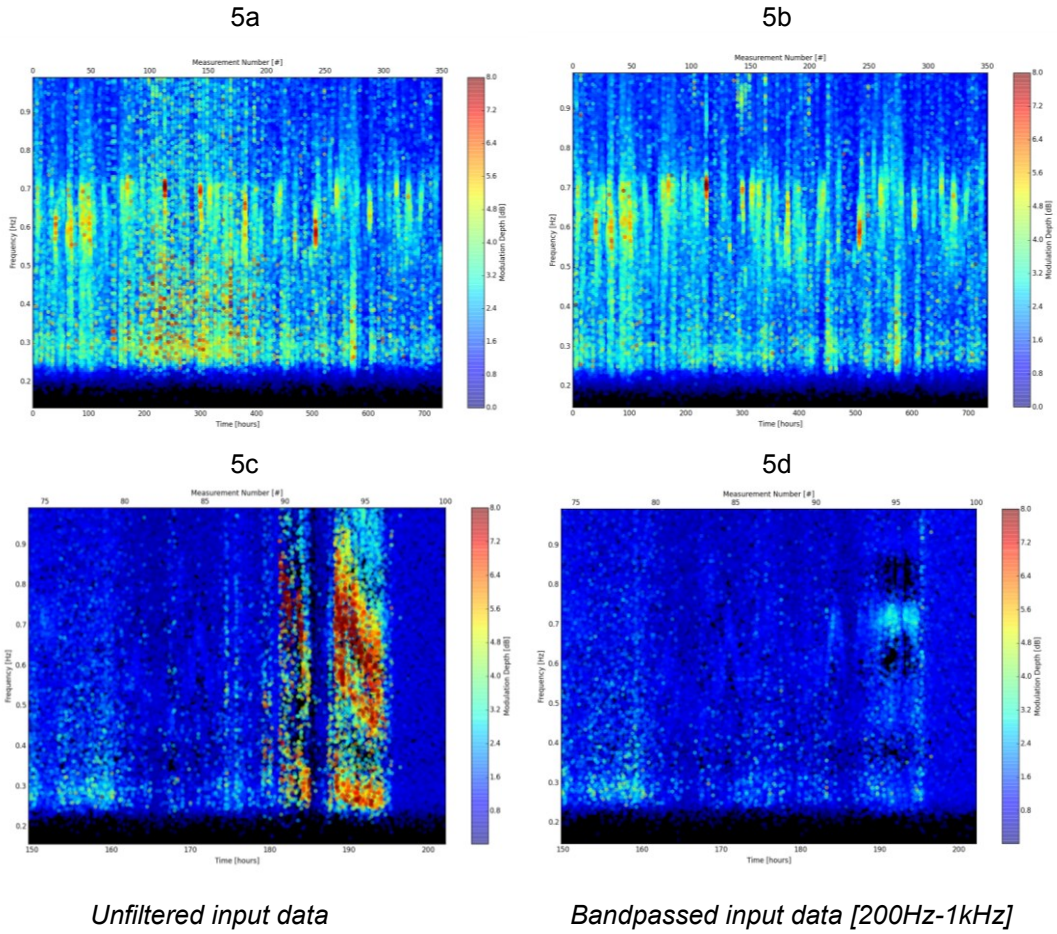

Figure 7: Effect of a bandpass filter on the input data. The figure on the left is the original data, and the figure on the right is the same data bandpassed from 200Hz to 1000Hz

Figure 8 illustrates how bandpass filtering can successfully remove a great deal of extraneous noise. Figure 8a-d show a dramatic change in the modulation spectrogram before and after filtering. Figure 8c in particular represents part of a measurement where the modulations from frogs croaking dominated the spectrogram. Figure 8d is the same measurement section that has been bandpassed before analysis. As is apparent in the figures, the contribution of the frogs was removed completely, revealing modulations around the turbine BPF that were previously undetected. The method of bandpassing the input sound recording was found to be very effective at removing noise from insects and small fauna, which typically create significant modulations with high frequency content.

4.2 Prevalence of Strong Amplitude Modulation

The effect of wind turbine AM on annoyance to a listener was found by Hünerbein et al to be strongly affected by contextual and attitudinal aspects of a particular listener [3]. New Zealand standard NZS 6808:2010 – one of the few standards that specify a penalty scheme for wind turbine AM – uses an overall modulation depth of 5dB as the threshold to apply penalties [4].

Using a threshold of 5dB, the rate of occurrence for strong amplitude modulation was determined by calculating the probability density function of the modulations occuring near BPF across the entire measurement time at each receptor. Figure 8 and Figure 9 plot the probability density and cumulative probability distribution of modulation depth around the wind turbine BPF from the data in Figure 4.

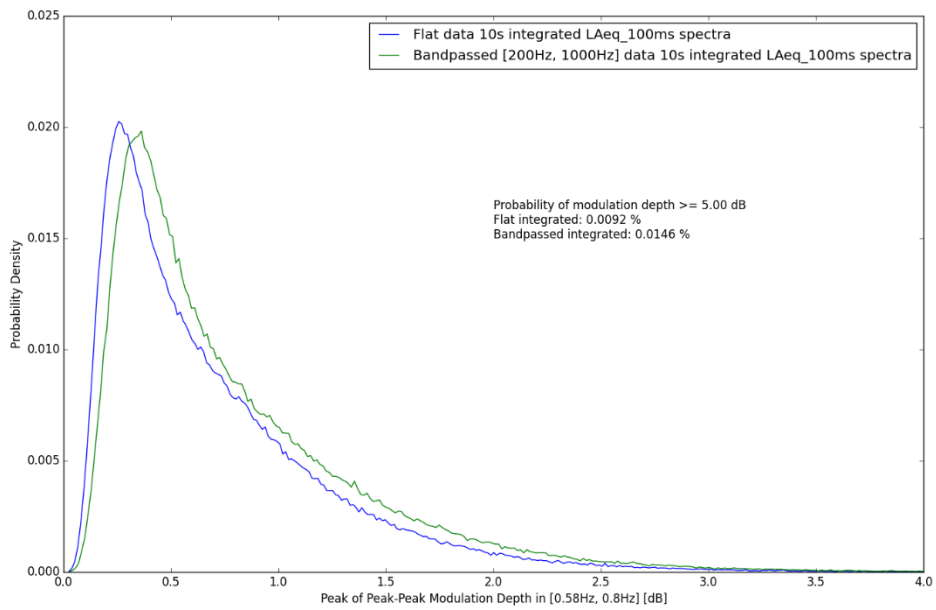

Figure 8: Probability density of modulation strength between 0.58Hz and 0.8Hz

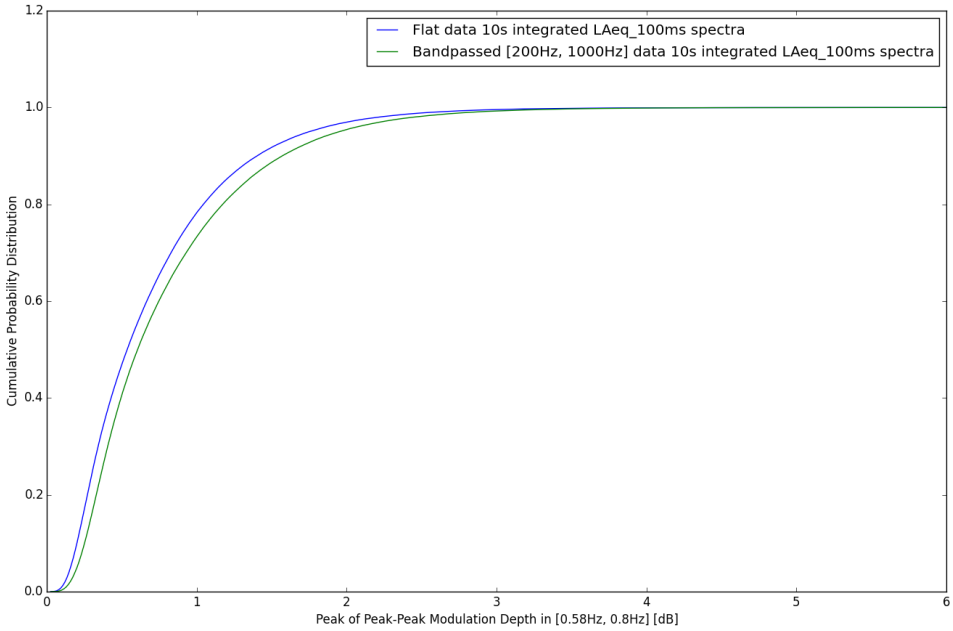

Figure 9: Cumulative probability distribution of modulation strength between 0.58Hz and 0.8Hz

Notable in these plots is the low probability of strong modulations even in data sets where a trend of amplitude modulation was visibly apparent. The most common modulation depths measured are less than 1dB and in the above measurement, modulations greater than 5dB accounted for less than 0.015% of the total recording time. The highest calculated rate of occurrence of modulation depths greater than 5dB was approximately 0.25% of the total measurement time.

5 DISCUSSION

From the results shown above, the automatic detection algorithm was successful in detecting wind turbine amplitude modulation in a sound recording. The method of detection was found to be susceptible to modulations from ambient sources, with high contamination from strongly modulated sources such as insects; however, modulating sources composed of high frequencies – such as insects and small fauna – were readily filtered by bandpassing the input sound recordings. Ambient sources that modulate with lower frequency content, such as traffic and wind noise, were not as easily filtered and could obscure AM from a wind turbine. There is currently no way, other than listening to the sound recording, to distinguish between wind turbine AM and ambient noise that is modulating at the wind turbine BPF.

The wind farms that had the strongest modulation depths were from farms that had a lower number of turbines. One hypothesis for this is that multiple turbines all modulating with random phase will smooth out the peaks and troughs that one might see from a single turbine. However, the sample size of large and small wind farms in this study is not sufficient to make any definitive conclusions with respect to AM prevalence and wind farm size.

The greatest modulation depths were detected from the turbines with the largest blade diameters. This reconciles well with the work done by Bullmore et al who hypothesized that wind turbine AM could be generated by partial stall along the length of the blade [5]. Larger blades combined with high wind shear conditions would experience a greater range of wind speeds than smaller blades.

6 CONCLUSION

A modification of the algorithm developed for RenewableUK was applied to a large amount of measured data obtained from five different wind farms in Southern Ontario, Canada. The algorithm was successful in detecting AM in a number of cases where modulation was audible in the sound recordings. The algorithm benefited greatly from filtering of the input data, removing the modulations from high frequency sources such as insects and small fauna.

The output of the algorithm was used to assess the rate of occurrence of AM depths greater than 5dB. Modulations of this magnitude were detected in, at most, 0.25% of the total measurement time.

7 NEXT STEPS

This work represents a preliminary analysis of a modified automatic detection algorithm based on the method developed for RenewableUK. There are a number of areas for improvement in future iterations. Next steps include:

- Decrease the time interval for the A-weighted level vs. time analysis. This would help minimize artificial harmonics generated due to low sampling frequencies.

- Modification of the FFT algorithm to calculate accurate peak-peak amplitude spectra directly, instead of using an intermediate PSD calculation. The aim being to reduce the reliance on integration to scale the amplitudes of the FFT spectra.

- A more robust method of noise rejection. Bandpassing the input recordings from 200Hz to 1kHz works well to eliminate some contamination from ambient sources, however, it is ineffective at removing ambient sources who's frequency components fall inside the range of the bandpass filter.

- Analysis and collaboration of other techniques to detect wind turbine AM. Examples include the Cooper and Evans method of analysis based on the 1/3rd octave band spectra [6], and the Tachibana method which examines the difference between the levels measured using a fast (125ms) and slow (1s) integration time constant [7].

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