Wind farm noise amplitude modulation and its acceptability for sleep

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Dedicated
to

My parents
and Cham

Acknowledgements

Personal

First and foremost, I want to thank my supervisor, Kristy Hansen. It has been an honour to be her student. She has taught me, both consciously and subconsciously, how good environmental acoustics is done. I appreciate all her contributions of time, ideas and patience to make my study experience productive and stimulating. The joy and enthusiasm that she has for her research was contagious and motivational for me, even during the tough times in my study. I am also thankful for the excellent example she has provided as a female acoustician and lecturer.

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Last, I would like to thank my family for all their love and encouragement. I thank my parents who raised me with a love of science, and who supported me in all my pursuits. Thank you.

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Abstract

Wind farm noise amplitude modulation (AM) is defined as a periodic variation in the amplitude of the noise which occurs at the blade-pass frequency, which is a unique characteristic of the noise. This phenomenon is a source of complaints due to its potential to cause annoyance and sleep disturbance. Here, to analyse AM, I proposed several modifications to the algorithm developed by the UK Institute of Acoustics, which was developed only recently and is one of the best algorithms available to date. I then used the modified algorithm to characterise the AM measured at several locations near South Australian wind farms. To prepare stimuli for laboratory experiments, I used the measured AM characteristics to synthesise AM stimuli. During the experiment, AM was also investigated in terms of its level of acceptability for sleep. I found that AM is audible both outdoors and indoors up to several kilometres from a wind farm. Also, AM characteristics depend on meteorological and operating conditions. The listening test results showed that synthesised AM stimuli are indistinguishable from measured AM samples, indicating that using synthesised noise for laboratory studies is suitable. Furthermore, I found that an increase in the variation in the amplitude of the noise (AM depth) at a high level of a tone (tonal audibility) is associated with lower acceptability for sleep for noise-sensitive individuals. Further research is needed to understand the seasonal and diurnal characteristics of AM and its effect on annoyance and sleep disturbance.

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List of Abbreviations

AM	Amplitude modulation of wind farm noise
WFN	Wind farm/turbine noise.
IOA	The Institute of Acoustics, UK
BGN	Background noise
IFFT	Inverse fast Fourier transform
SPL	Sound pressure level
LFN	Low frequency noise
dBA	A-weighted sound pressure level
BPF	Blade-pass frequency
ROC	Receiver operating characteristic
AUC	Area under the curve
AISH	The Adelaide Institute for Sleep Health
SDT	Signal detection theory

You don't have to be great to start;
but you have to start to be great.

— Zig Ziglar

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Introduction

Contents

1.1 Amplitude modulation of wind farm noise

Amplitude modulation (AM) is defined as a periodic variation in the amplitude of the noise which occurs at the blade-pass frequency in the case of wind turbines. [1, 2]. The frequency content in the noise signals depend on the distance from a wind farm to the receiver. For example, broadband AM occurs at mid- to high frequencies (usually higher than 400 Hz) and it manifests as a 'swishing' noise [2]. This type of AM is apparent close to a turbine. The second type of AM occurs at the low frequency range and is described as a "thumping" noise. It is referred to as other AM or enhanced AM and can be heard from wind farms across. [3] (see Figure 1.1).

Low frequency AM has two types: one in which a single – frequency sound is modulated (hereafter termed tonal AM) and another in which broadband sound

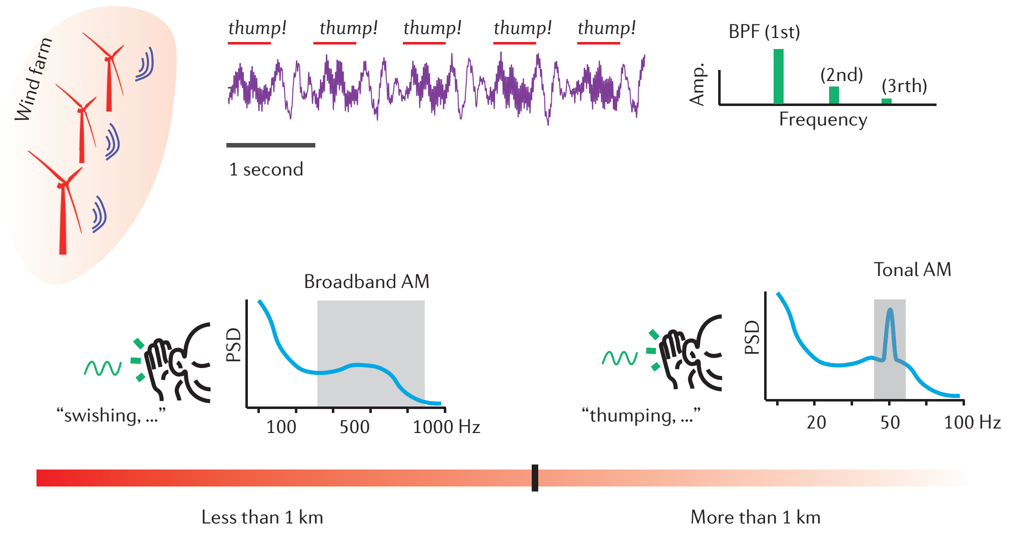

Figure 1.1: The AM of wind farm noise. Wind farms generate noise which shows a periodic variation in amplitude at the blade-pass frequency. Two types of AM can be heard at different distances from a wind farm.

is modulated by one or several frequencies related to the turbine blade – pass frequency. For the broadband AM sound, the generation mechanism could be transient stall which can be reduced by blade pitch control [3, 4]. However, for the low-frequency tonal AM, the mechanism of this phenomenon has not yet been addressed sufficiently in the literature.

AM is a unique characteristic of wind farm noise (WFN), which has contributed to annoyance [5–10], and it has been hypothesised to impact sleep disturbance [11]. However, clear evidence of whether wind farm noise is associated with sleep disturbance and health effects is still not established. Adequate data regarding the physiological effects of AM are presently lacking.

1.2 Motivation

During a study by the South Australian Environmental Protection Agency in 2013, at least 14 (out of 15) residents living at various distances of up to 8 km complained of 'thumping' and/or 'rumbling'. Their responses were documented in noise diaries that were collected over several weeks and were provided to our research group. While many people believe that the residents complain about the wind farm because they are unhappy with the lack of financial compensation they receive compared to their neighbours who are hosting the turbines, others believe that the noise can propagate several kilometres away from a wind farm. The influence of wind farm noise on humans is an ongoing debate, and it is not possible to usefully take part in this debate without having a detailed understanding of the noise. These factors motivated me to conduct this Master's project to contribute to the understanding of wind farm noise.

1.3 Aims

The overall aim of this master's thesis is to determine how often wind farms generate the low-frequency tonal AM and whether it affects humans through annoyance and/or sleep disturbance. This will be done through addressing the following objectives:

1. to detect, quantify and characterise the low-frequency tonal AM of wind farm noise measured at several locations near South Australian wind farms

2. to evaluate the quality of synthesised AM stimuli in comparison to measured noise in order to verify that the synthesised signals are suitable for laboratory experiments

3. to investigate the effects of low-frequency tonal AM on the acceptability of the noise for sleep via laboratory listening tests.

1.4 Thesis outline

The main text consists of the present introductory chapter followed by five other chapters that systematically present the results of field data analyses and laboratory experiments (see Figure 1.2).

Chapter 2 reviews previous work on the detection and quantification of AM, long-term studies of AM, AM synthesis methods and its potential to cause annoyance and sleep disturbance. Chapter 3 presents the characteristics of wind farm noise AM measured at 10 residences at two wind farms in South Australia. This chapter

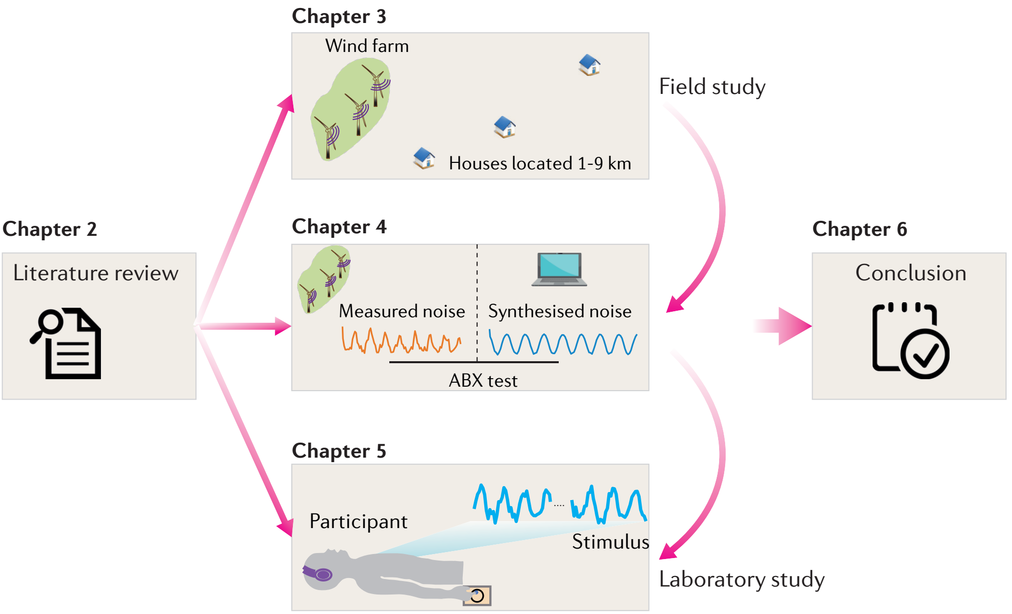

Figure 1.2: Illustration of the structure of the thesis. Chapter 2 reviews previous work on AM, including field and laboratory studies. Chapter 3 presents field study results that are used as input information for Chapter 4. The results from Chapter 4 are used for Chapter 5, which studies the effects of AM on the acceptability for sleep. Chapter 6 summarises all key findings of the thesis.

addresses the first aim of this study. Chapter 4 describes the methods for synthesising AM and evaluates the quality of the synthesised stimuli. The second aim of the project is addressed in Chapter 4. In Chapter 5, the synthesised stimuli in Chapter 4 are used to investigate the effects of AM on the acceptability for sleep, which addresses the third aim of the project.

1.5 Contributions

This study provides important knowledge regarding AM and its acceptability for sleep. Several noteworthy contributions include:

1. proposing modifications to the IOA ‘Reference method’ for analysing the amplitude modulation of wind farm noise that show superior performance compared to the original method for noise data measured at distances greater than 1 km
2. characterising AM measured at distances greater than 1 km for the first time.

3. evaluating the quality of the synthesised stimuli that are used for laboratory experiments; the synthesised AM stimuli are to faithfully represent the real noise

4. proposing a new methodology and testing the acceptability of AM for sleep, in which higher modulation depth and tonal audibility are shown to produce higher annoyance and sleep disturbance.

1.6 Publications

During this master's project, I published and submitted the following publications:

Journal papers

1. **Nguyen DP** , Hansen K, Zajamsek B. Human perception of wind farm vibration.*Journal of Low Frequency Noise, Vibration and Active Control* (Online 2019 Apr 2). (Q1, IF = 1.49, SJR:11/88). DOI: `https://doi.org/10.1177/1461348419837115` [**Published**]

2. Hansen KL, **Nguyen DP**, Zajamšek B, Catcheside P, Hansen CH. Prevalence of wind farm amplitude modulation at long-range residential locations. *Journal of Sound and Vibration.* Volume 455, 1 September 2019, Pages 136-149 (Online 2019 May 13). (Q1, IF = 3.123, SJR:2/88). DOI: `https://doi.org/10.1016/j.jsv.2019.05.008` [**Published**]

3. **Nguyen DP**, Hansen K, Zajamsek B, Catcheside P. Evaluation of wind farm noise amplitude modulation synthesis quality. *Applied Acoustics* . 09/2019 (Q1) [**Under review**]

Peer-reviewed conference papers

1. **Nguyen DP**, Hansen K, Zajamsek B. Characterizing tonal amplitude modulation of wind farm noise. *In Proceedings of ACOUSTICS 2018 Nov (Vol. 7, No. 9).* `https://www.acoustics.asn.au/conference_proceedings/AAS2018/papers/p101.pdf` [**Published**]

2. Hansen K, **Nguyen DP** , Zajamsek B, Micic G, Catcheside P. Pilot study on perceived sleep acceptability of low-frequency, amplitude modulated tonal noise. *23rd International Congress on Acoustics, Aachen, Germany, 2019 September 8-13.* `http://pub.dega-akustik.de/ICA2019/data/articles/000499.pdf` [**Published**]

3. **Nguyen DP**, Hansen K, Zajamsek B. Wind farm infrasound detectability and its effects on the perception of wind farm noise amplitude modulation. *In Proceedings of ACOUSTICS 2019 Nov 9.* [**Accepted**]

4. Hansen K, **Nguyen DP**, Lechat B, Zajamsek B, Alamir M, Micic G and Catcheside P. Comparison between annoyance due to traffic noise and wind farm noise in a non-focused listening test. *In Proceedings of ACOUSTICS 2019 Nov 9.* [**Accepted**]

The only way to do great work
is to love what you do.

— Steve Jobs

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Review of literature

Contents

2.1 Detection and quantification of AM

Listening to audio files by experts is an appropriate approach for AM detection. However, this approach is a subjective and slow process when applied to the large data sets, and thus several automated methods of AM detection have been developed to speed up this process. They can be separated into three categories: time-domain [12, 13], frequency-domain [6, 14] and 'hybrid' methods which combine time and frequency domain methods [2, 9, 15, 16]. The time-domain methods are easy to implement and require minimal post-processing. They are convenient, even for individuals with no acoustics training. However, these methods do not perform well on data that are contaminated by extraneous noise. Compared with time-domain methods, frequency-domain methods can work well in cases where data are highly contaminated by other noise sources; however, there are some disadvantages of these methods. These methods are slightly more complex to implement and require signal-processing skills. Also, due to the averaging process associated with the frequency-domain methods, the resulting spectra contain only frequencies at which periodic amplitude variation (AM) occurs; it is thus not possible to detect random amplitude variations using these methods. Finally, the value of AM depth, or degree of AM, obtained using these methods is not an intuitive measure of AM. To overcome these drawbacks of time- and frequency- domain methods, hybrid methods have been developed, which have advantages such as reliably identifying modulation at the blade-pass frequency in the frequency domain and maintaining a realistic measure of the modulation depth through analysis in the time domain. These methods can be used to batch process data, but the coding can be challenging. Since hybrid methods focus on modulation at the blade-pass frequency and harmonics [2], these methods cannot detect random amplitude variation.

However, the performance of many AM detection algorithms has not been evaluated rigorously. Owing to a lack of gold-standard data sets, these current AM detection algorithms are only validated based on visual inspection, which does not reveal their performance in terms of correct detection of AM and correct rejection of non AM. Hansen et al. [1] suggested that listening to audio files is an appropriate approach to establish a gold-standard data sets for validating AM detection algorithms. Furthermore, many of these AM detection methods were developed with the intention of identifying swishing noise, which is amplitude-modulated, mid- to high-frequency noise. AM identification becomes a more difficult task for low-frequency noise because the AM signals are very weak and often contaminated by other noise sources. Although there has been some testing of automated AM detection in swishing noise, the performance of the most commonly used methods in low-frequency AM is questionable [17]. Therefore, several modifications are needed to apply these methods for detecting low-frequency AM.

2.2 Long-term studies of AM

Although wind farm AM is gradually becoming a source of interest in wind farm noise studies, information regarding long-term studies of this phenomenon is rare in the literature. To evaluate the effects of various meteorological conditions on AM, Larsson et al. [18] measured acoustical and meteorological data continuously for two years in two areas in Sweden. The authors concluded that AM occurs more often under certain meteorological conditions, such as stable atmospheric conditions. AM was also observed between 20% and 30% of the operational time, which depended on the distance from wind farms. To evaluate the effects of wind speed and wind direction on AM, Paulraj et al. [19] demonstrated that although the AM depth depends on wind direction, there is no relationship between AM depth and wind speed. AM most often occurs during winter (October-December in Finland). The noise and weather data were collected continuously for one year at 1.1 km from the nearest wind turbine. Conrady [20] recently analysed long-term data measured in Sweden and found that AM occurrence depends on both annual and diurnal variations. Consistent with previous studies [3, 18], the author found that AM occurs more often during the night and early morning than during noon and the early afternoon. AM was most often observed in November and January, and less often during spring.

However, previous studies focus on broadband AM which occurs at mid- to high frequencies. The prevalence and characteristics of low-frequency tonal AM, which usually occurs at distances greater than 1 km from wind farms is still lacking. This information is relevant in the context of Australian wind farm noise, where residents usually live more than 1 km from wind farms. The relationship between distance and AM prevalence has also not been reported in the literature to date.

2.3 Method for synthesising AM

Measured data are usually contaminated by other noise sources, such as traffic noise, birds and agricultural activities [1]. Synthesised WFN stimuli have been used preferentially in laboratory experiments [8, 10, 21]. Using synthesised stimuli allows the experimenter to flexibly adjust the noise parameters, such as the modulation frequency and AM depth. Also, the characteristics of wind farm noise (i.e., tonality, low-frequency noise and AM) can be easily isolated for separate investigations.

There are some different methods for synthesising the AM of wind farm noise, and a common technique used to synthesise wind farm AM is to assume a combination of two components: the wind farm noise spectrum without AM, from here on termed background noise (BGN) and the amplitude modulated tone (AT), as follows [6–9]

$$WFN_{AM} = \beta \times (AT + \alpha \times BGN) \tag{2.1}$$

in which β is used for controlling the overall sound pressure level (SPL) and α is used for adjusting the level of background noise (masking noise).

For modelling environmental noise, the power-law ($1/f^{\gamma}$) is commonly used [22]. According to this law, the relationship between the log power spectral density and log frequency is linear. Pink-noise ($1/f$) is usually used for the synthesis of BGN in general because pink-noise is known to occur in a wide variety of natural physical environments [23]. The noise power-law was used by Yokoyama et al. [7] for synthesising typical WFN spectra, in which the authors used a linear spectrum with slopes of -4 dB/octave. Another approach was used by Lee et al. [6], in which the real noise sample was transformed to the frequency domain; a moving average filter was then applied to extract the general noise spectrum; the general spectrum was then multiplied with the white noise spectrum; and then the derived product was transformed to the time domain using an inverse fast Fourier transform (IFFT) to create the background noise sample.

There are two common approaches used to synthesise AT [1, 9]. These approaches only differ in their use of modulating signals. While the modulating signal used in the first method is a sine wave, a Gaussian wave is used in the latter. The use of a Gaussian wave allows accurate representation of the real characteristics of AT (i.e., asymmetric pulse shape), although the number of input parameters required for the synthesis is higher in comparison with the use of a sine wave.

Although the advantages of using synthesised stimuli in laboratory experiments have been highlighted in previous studies, information regarding the extent to which the synthesised noise represents real WFN is still lacking.

2.4 Annoyance and potential sleep disturbance

Previous listening tests have revealed that annoyance ratings depend on AM characteristics, such as AM depth or modulation frequency [5–10]. Although the increase in AM depth is consistently reported to increase annoyance ratings, there is no current consensus on the effect of modulation frequency [8, 9]. Listening tests using synthesised WFN based on measurements taken between 100 m and 1 km showed that low-frequency components less than 63 Hz have minimal effect on perceived loudness [24]. However, these results may not extrapolate to all WTN measured at distances greater than 1 km, where the spectrum is dominated by low-frequency energy.

Low-frequency amplitude modulated tonal noise can adversely affect performance for tasks involving an increased level of attention and awareness for a relatively long time of 30 minutes [25]. Also, low-frequency noise and the associated lower cortisol levels were found to be related to tiredness and negative mood [26]. Although the stimuli used in these studies were from other noise sources (i.e., low-frequency ventilation noise containing a tone in the 31.5 Hz 1/3-octave band and at a higher level than realistic wind farm noise), these studies are relevant in the study of wind farm noise, which can contain similar characteristics. For instance, AM observed at large distances from wind farms is also dominated by low-frequency, and contains low-frequencies tones modulated by the blade pass frequency.

Regarding the effects of WFN on sleep, a recent comprehensive review can be found in Micic et al. [11]. The level of wind farm noise is relatively low compared to other types of environmental noise. However, differences in the characteristics of the noise (i.e., low-frequency content, tonality and AM) can result in annoyance or sleep disturbance [27, 28]. Current limits for wind farm noise are based on data from studies that focused on other environmental noise sources. Wind farm noise has unique and persistent characteristics which might make it more disturbing than other noise types, particularly at night-time in a normally quiet rural area.

However, clear evidence for whether wind farm noise is associated with sleep disturbance and health concerns is still not yet established. Also, data regarding the physiological effects of low-frequency noise (LFN) on humans are lacking up to now. Comprehensive future investigations are necessary to answer these unclear questions regarding wind farm noise.

2.5 Summary

Although several methods have been developed to detect and quantify AM, they were originally developed for analysing broadband AM. Also, these methods have not been validated properly. Therefore, the performance of these methods is questionable when they are applied to low-frequency tonal AM, which is the main focus of this study.

A few recent studies have characterised broadband AM measured at distances less than 1 km from wind farms, no studies characterised the low frequency tonal AM that usually occurs at distances greater than 1 km from a wind farm. Furthermore, most of previous studies were conducted in cold climate where have a long winter covered with ice. These conditions differ to Australia's climate, especially in South Australia where have a Mediterranean climate with mild wet winters and hot dry summers. The differences in climate can affect the propagation of the noise, and thus alter the AM characteristics.

Regarding laboratory experiments assessing the annoyance and sleep disturbance potential of AM, synthesised stimuli are commonly used. However, information regarding how well these synthesised stimuli represent the real noise is still lacking.

Finally, previous studies on human perception have also focused on broadband AM rather than tonal AM, although the latter has been more consistently measured at several wind farms in South Australia at distances greater than 1 km. It is also unknown whether acceptability for sleep is judged differently to annoyance or if wind farm noise containing AM may be more problematic for sleep than other noise types.

The only thing greater than the power of the mind is the courage of the heart.

— John Forbes Nash

3

Characterisation of wind farm noise amplitude modulation

Contents

Part of the research contained in this chapter has been published:

1. **Nguyen DP**, Hansen K, Zajamsek B. Characterizing tonal amplitude modulation of wind farm noise. *In Proceedings of ACOUSTICS 2018 Nov (Vol. 7, No. 9).* `https://www.acoustics.asn.au/conference_proceedings/AAS2018/papers/p101.pdf` [**Published**]

2. Hansen KL, **Nguyen DP**, Zajamšek B, Catcheside P, Hansen CH. Prevalence of wind farm amplitude modulation at long-range residential locations. *Journal of Sound and Vibration*. Volume 455, 1 September 2019, Pages 136-149 (Online 2019 May 13). (Q1, IF = 3.123, SJR:2/88). DOI: `https://doi.org/10.1016/j.jsv.2019.05.008` [**Published**]

(The Statement of Contribution forms are provided in Appendix A)

3.1 Introduction

The aims of this chapter are twofold: 1) to compare AM characteristics (i.e., AM depth and AM prevalence at two wind farms) and 2) to investigate the relationship between AM characteristics and meteorological (i.e., wind speed), geophysical (distance to wind farm) and operating (wind farm power output) conditions. I begin with a description of field data collection and then describe the method for analysing the data. I then discuss the different characteristics of AM at two wind farms. Finally, I present the relationship between AM characteristics and the aforementioned factors which can affect AM characteristics. These characteristics have important implications for possible sleep disturbance from wind farm AM, which I investigate in Chapters 4 and 5.

3.2 Data collection

3.2.1 Measurement locations

To compare AM characteristics at two wind farms (see Section 3.4.1), measurements were carried out inside two dwellings located 3.1 km from the Hallett-V wind farm and 3.4 km from the Waterloo wind farm both of which are located in South Australia, as shown in Figure 3.1. I hereafter refer to Hallett-V and Waterloo wind farms as Wind farm 1 and Wind farm 2, respectively. The measurement was carried out for 26 days at Wind farm 1 and for 7 days at Wind farm 2. A summary of wind farm information is outlined in Table 3.1.

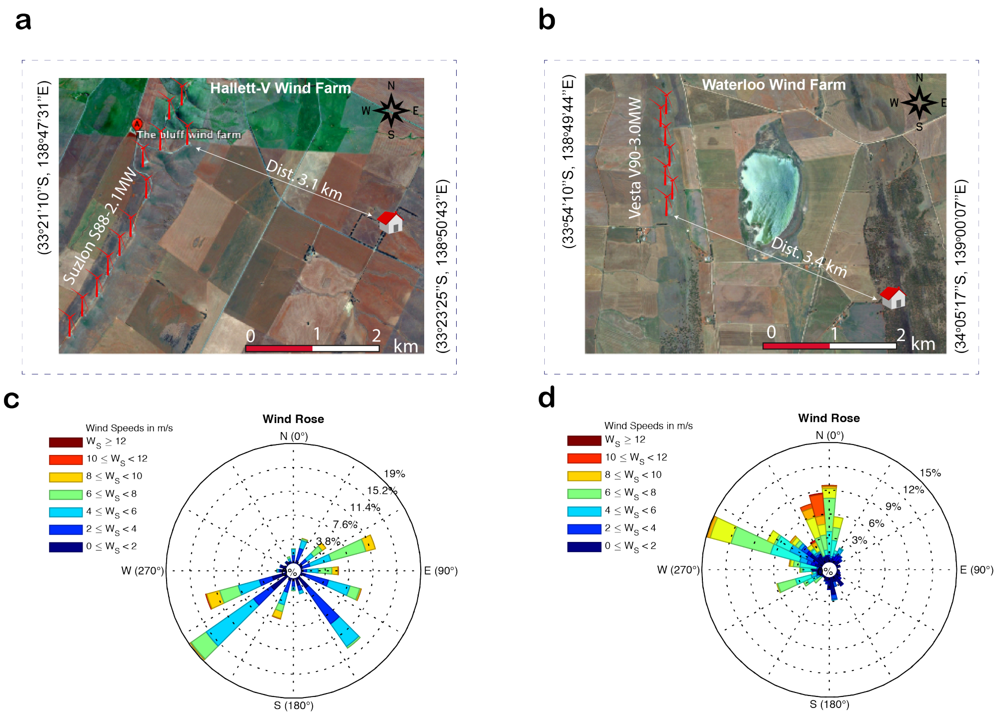


Figure 3.1: Measurement locations at two wind farms. **a**, Measurement at Hallett-V wind farm (Wind farm 1). **b**, Measurement at Waterloo wind farm (Wind farm 2). Only the nearest wind turbines to the dwelling are shown in a and b. **c,d**, Wind speed and wind direction during the measurement period at Wind farm 1 and 2, respectively.

Table 3.1: A summary of wind farm information

Name	Type of turbine	No. of turbines	Power capacity
Hallett-V (Wind farm 1)	Suzlon-2.1MW	25	52.5 MW
Waterloo (Wind farm 2)	VestasV90-3.0MW	37	110 MW

To investigate the relationship between AM characteristics and meteorological, geophysical and operating conditions (see Section 3.4.2), both indoor and outdoor noise were measured at nine houses located between 1.3 and 8.8 km from the nearest wind turbine of Wind farm 2, as shown in Figure 3.2. Wind farm 2 is positioned along the top of a ridge, with the wind turbine hub height relative to the houses varying between 85 and 240 m.

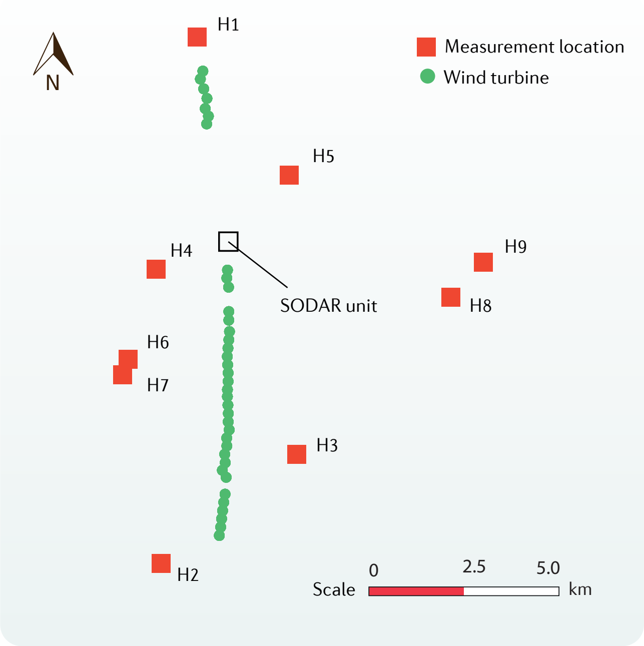


Figure 3.2: Measurement at Wind farm 2. Nine residences located between 1.3 (H1) and 8.8 km (H9) from the nearest turbine. The location of the SODAR unit which was used for collecting meteorological data is also shown.

3.2.2 Instrumentation and measurement set-up

Outdoor noise was measured using the National Instruments 9234 data acquisition system at 10240 Hz sampling frequency. The outdoor microphone was a G.R.A.S type 40AZ with a 26CG preamplifier, which has a noise floor of 16 dB(A) and a flat frequency response down to 0.5 Hz. A typical outdoor measurement set-up is shown in Figure 3.3. The outdoor microphone was mounted at a height of 1.5 m and protected using a spherical secondary windscreen with a diameter of 450 mm. To minimise façade reflections and wind-induced vegetation noise, the outdoor microphone was positioned at least 20 m away from the dwelling and at least 10 m from surrounding vegetation.

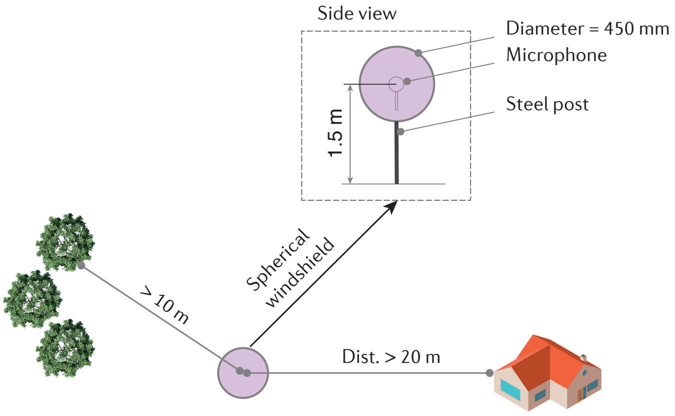


Figure 3.3: Typical outdoor measurement set-up.

Indoor noise was measured using Bruel and Kajer LAN-XI Type 3050 data acquisition systems at 8192 kHz sampling frequency. The indoor microphone was a B&K type 4955, which has a noise floor of 6.5 dB(A) and a flat frequency response down to 6 Hz. The indoor microphone used in the analysis was mounted on a mini tripod and positioned approximately 100 mm from a room corner, at the intersection between two walls and the floor. The indoor measurements of all residences were taken in a room that faced the wind farm, and the windows were closed.

A total of 8716 and 8972 10-minute samples of outdoor and indoor data, respectively, were analysed in this study. The number of 10-minute samples taken outdoors and indoors at each residence is shown in Table 3.2.

Table 3.2: Number of 10-minute samples used for analysis.

House	H1	H2	H3	H4	H5	H6	H7	H8	H9
Distance (km)	1.3	2.3	2.4	2.5	3.3	3.4	3.5	7.6	8.8
Outdoors	833	700	471	1548	1087	640	1659	999	848
Indoors	834	803	860	1561	1091	640	1344	989	850

The hub-height wind speed data for the nearest wind turbine to each residence were available from the wind farm operator for all residences except H5, for which the hub height data were measured using a Fulcrum 3D SODAR. The SODAR was located on the same ridge-top as the wind turbines, as shown in Figure 3.2. The resolution of this device is ±0.01 m/s, according to the manufacturer. Power output data for the wind farm were obtained from the Australian Energy Market Operator website [29] in five-minute averages. These data pertain to the entire wind farm and data for each individual wind turbine were not available.

3.3 Signal analysis technique

3.3.1 AM detection algorithm

To detect and quantify AM, I used the 'Reference method' which has been developed by the Institute of Acoustics (IOA) (hereafter referred to as the IOA method). The IOA method has been developed for detecting and quantifying broadband AM occurring at mid-to high- frequencies. To apply this method to our data, which contained the low-frequency tonal AM, several modifications to the IOA method were required, as shown in Figure 3.4 (hereafter referred to as the modified IOA method). These modifications included:

1. Instead of using a broad bandwidth, this study used 1/3-octave bandwidth.

2. The calculation of the equivalent sound pressure level (SPL) was based on unweighted rather than A-weighted time series data.

3. The prominence factor specified in the IOA method was reduced from four to three.

4. The tonal audibility and normal-hearing threshold curve, as outlined in the IEC 61400-11 [30] and ISO 389-7 [31] respectively, were taken into account for quantifying AM.

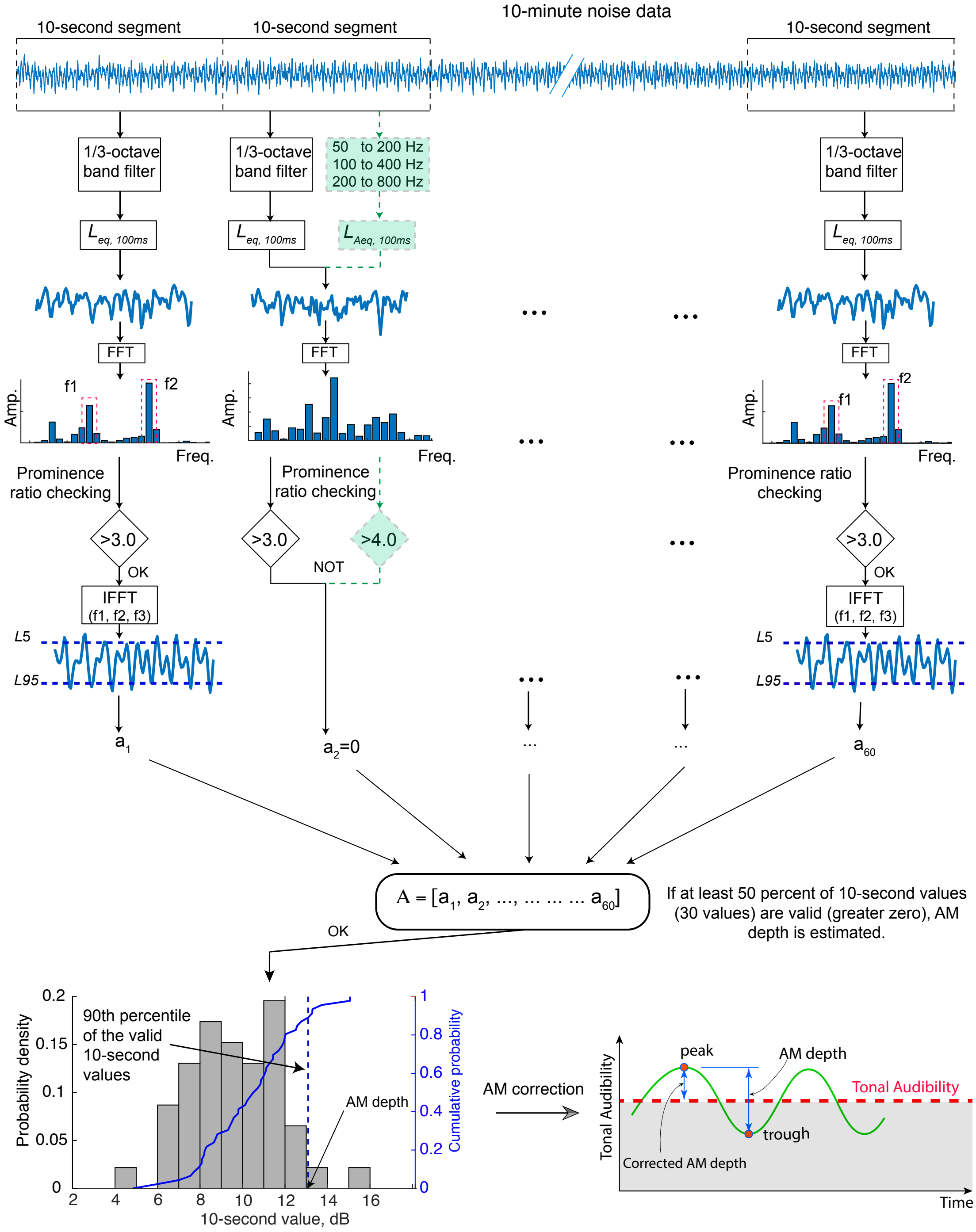


Figure 3.4: Method for detecting and quantifying AM. The value in the boxes shaded green with dashed gray outlines are the original values used in the IOA method.

3.3.2 Validation of AM detection algorithm

To evaluate the performance of the modified IOA method, I compared the AM detection output of two methods (i.e., the original and the modified IOA method) to a gold-standard data set. To construct the gold-standard data set, I visually inspected and classified 864 spectrogram segments which were randomly selected from the measured data. Figure 3.5a shows six segments, in which segments 1, 2 and 4 were classified as containing AM, while segments 3, 5 and 6 were classified as not containing AM. The segments containing AM are visible as horizontal lines in the spectrum, spaced vertically at the blade-pass frequency (BPF) of 0.8 Hz.

To compare the performance, a receiver operating characteristic (ROC) curve analysis [32] was conducted. The ROC curve is a graphical representation of performance. To construct the ROC curve, as shown in Figure 3.5b, the outcome of the AM detection algorithms were compared with the gold standard data set. A confusion matrix [33], as shown in Figure 3.5c, was then created, showing true positive and false positive detection rates. This process was repeated for each prominence factor, resulting in a ROC curve.

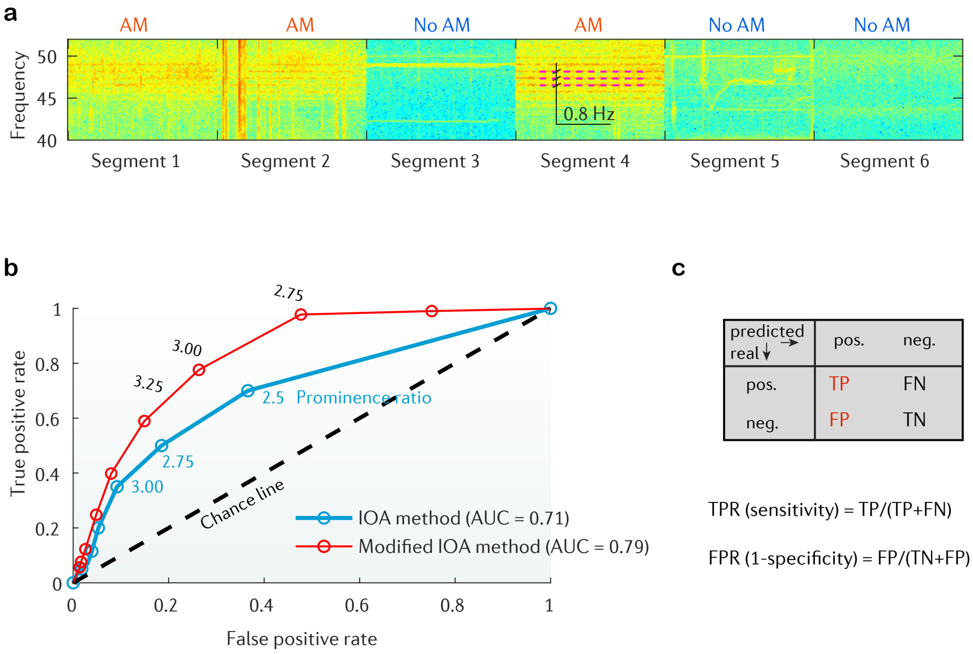


Figure 3.5: Validation of AM detection algorithm. **a**, Generation of gold-standard data set using spectrogram. **b**, ROC curve as a graphical representation of performance. **c**, Confusion matrix.

The ROC curve has two advantages: 1) the area under the curve (AUC) shows the overall performance of the algorithms and 2) an optimal prominence factor is also found on the graph. Overall, the performance of the modified IOA method (AUC = 0.79) is better than the original IOA method (AUC = 0.71). I found that the optimal prominence factor is three which is closet to the top left corner, a perfect performance point (i.e., TPR = 1 and FPR = 0). Using a prominence factor of three also is balance between false and true positive rates.

3.4 Results

3.4.1 AM characteristics at different wind farms

The mean AM depth for indoor noise measured at Wind farm 1 is lower in comparison to Wind farm 2, as shown in Figure 3.6. Narrowband analysis also revealed that while AM measured at Wind farm 1 occurs at 110 Hz, AM measured at Wind farm 2 occurs at 46 Hz. Although the difference in distance from the nearest turbine to the measurement locations is small, there are other factors that may have caused the difference in the characteristics of AM such as turbine types, meteorological and operating conditions as well as wind farm layout and topography. For example, the measurement location for Wind farm 1 is mostly under crosswind and upwind conditions Figure 3.1. In contrast to the measurement at Wind farm 1, the noise data for Wind farm 2 were measured mainly under downwind conditions.

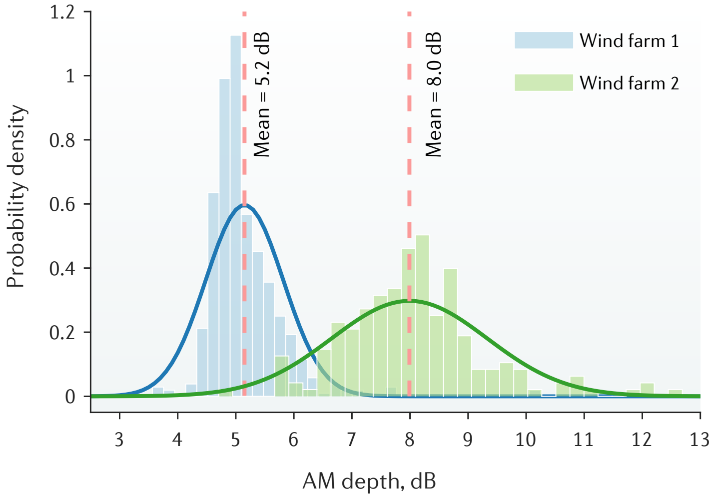


Figure 3.6: A comparison of AM depth between Wind farm 1 and 2.

To investigate the relationship between AM occurrence and wind farm percentage power capacity, I calculated the ratio between the number of samples containing AM and the total number of measured samples, as shown in Figure 3.7. While AM events were not dominant for any specific range of power output for the measured data at Wind farm 1, the peak percentage of AM events is observed when the wind farm percentage power capacity is approximately 40% for the measured data at Wind farm 2.

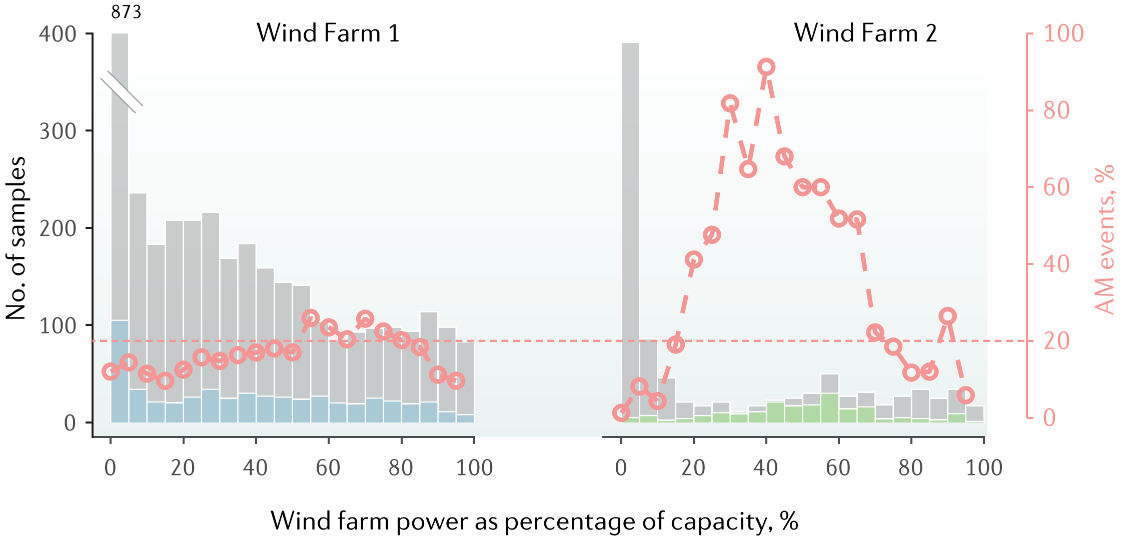


Figure 3.7: Relationship between AM occurrence and wind farm power output capacity. The gray bars correspond to the total measured samples and the green bars illustrate the detected AM samples. The red curve is the ratio between the detected AM and the total measured samples.

3.4.2 Prevalence and depth of wind farm AM

To investigate the prevalence and depth of AM occurring at a wind farm, I analysed noise data measured at nine houses located within 1.3 and 8.8 km of Wind farm 2 (Figure 3.2). I found that the mean AM depth for indoor noise was higher than for outdoor noise (8.5 dB compared to 7.8 dB). However, in contrast to the AM depth, the numbers of AM occurrences for indoor noise (2394 events) were fewer than those for outdoor noise (2890 events); this was approximately 33% for outdoor noise compared to 27% for indoor noise (Figure 3.8a).

Expectedly, the modulation frequency was consistently 0.8 Hz (Figure 3.8b), which corresponds to the blade-pass frequency when the wind turbines are operating at their nominal speed of 16.1 rpm. It is noted that to remain the natural characteristics of AM, the AM correction as shown in Section 3.3.1 and Figure 3.4 has not been applied to the AM depth and AM occurrence. However, in the next sections, the correction is applied to obtain a more realistic description of the AM characteristics, which takes into account the human hearing threshold.

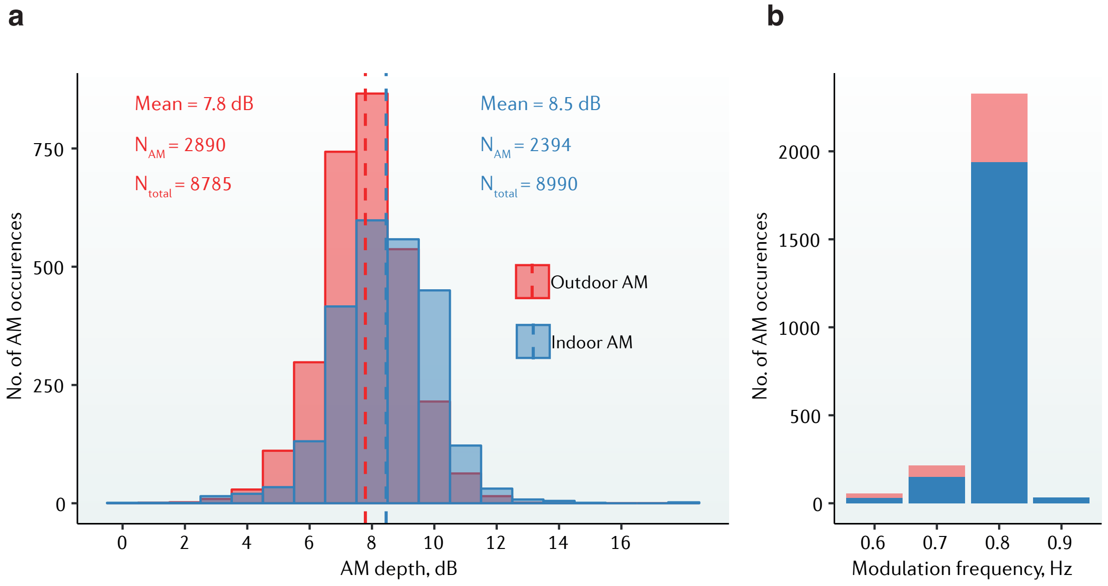


Figure 3.8: AM analysis of outdoor (red) and indoor (blue) noise measured at nine different residences located near a wind farm. **a**, Histogram of AM depth with a binwidth of 1 dB; The AM correction has not been applied. **b**, Histogram of modulation frequency with a binwidth of 0.1 dB.

3.4.3 Relationship between distance from the wind farm and AM

To investigate how often AM occurs at different distances from the wind farm, I calculated the proportion of time that the AM was present at each house. The data were then categorised into three groups (i.e., 1-2, 2-4 and > 4 km) to reduce the variance between measurement locations. I found that a trend of reducing AM percentage with distance is apparent for both before and after the AM correction, as shown in Figure 3.9. Interestingly, the occurrence of AM after 2 km is reduced by a factor of two. Also, as expected, applying the AM correction results in reducing the number of AM occurrences. The results show that the outdoor and indoor AM are still audible up to distances of 4 km for 24% (Figure 3.9a) and 16% (Figure 3.9b) of the time. At distances greater than 4 km, AM can be detected approximately 30% of the time outdoors and 20% indoors, although a large percentage of AM events are inaudible for a person with normal hearing.

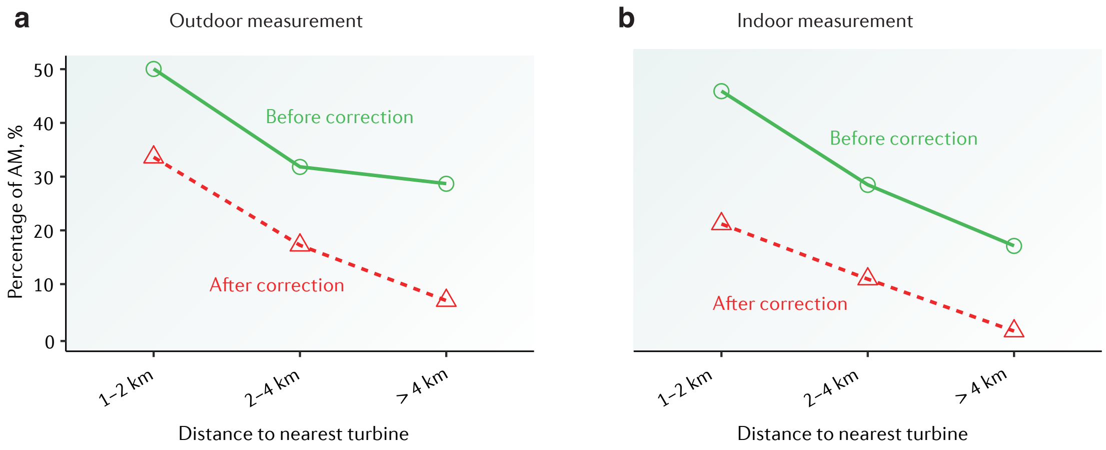


Figure 3.9: Relationship between distance and AM. The green and red lines show data before and after applying the AM correction. **a**, Outdoor AM and **b**, Indoor AM.

3.4.4 Wind farm operating conditions and AM

Wind farm power output and meteorological conditions are important factors which influence the AM characteristics. To show the relationship between these factors and AM, I constructed histogram plots as shown in Figure 3.10. I found that AM occurs more often when the wind farm is operating below its maximum rated power. The peak percentage of AM events is observed when the wind farm percentage power capacity is approximately 40% (Figure 3.10a) and when the hub-height wind speed is around 10 m/s (Figure 3.10b). Applying the AM correction shifts the peak percentage of AM to a higher wind farm power capacity and wind speed range, although audible tonal AM is still dominant at the percentage power capacity between 40 and 85%.

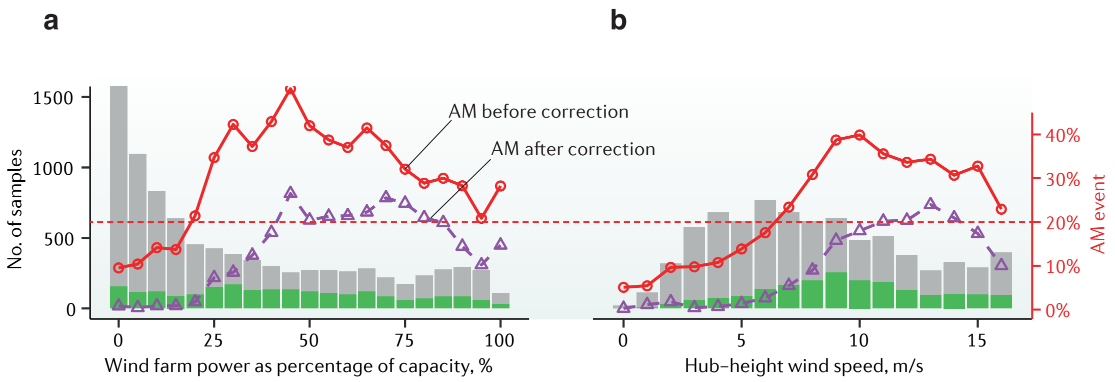


Figure 3.10: Relationship between AM occurrences and wind farm power output and hub-height wind speed. The gray and green bars correspond to the total measured samples and detected AM samples, respectively. The right y-axis is used for the line graph.

To investigate any association between the AM depth and percentage power capacity and hub-height wind speed, both linear and second order polynomial regression fits were used, although the correlation is poor (max $R^2 = 0.24$) (Figure 3.11a and b). I further tried to improve the correlation by separating the data into 2 km-wide distance bins, although the large scatter in the data points indicate that the correlation is still not improved.

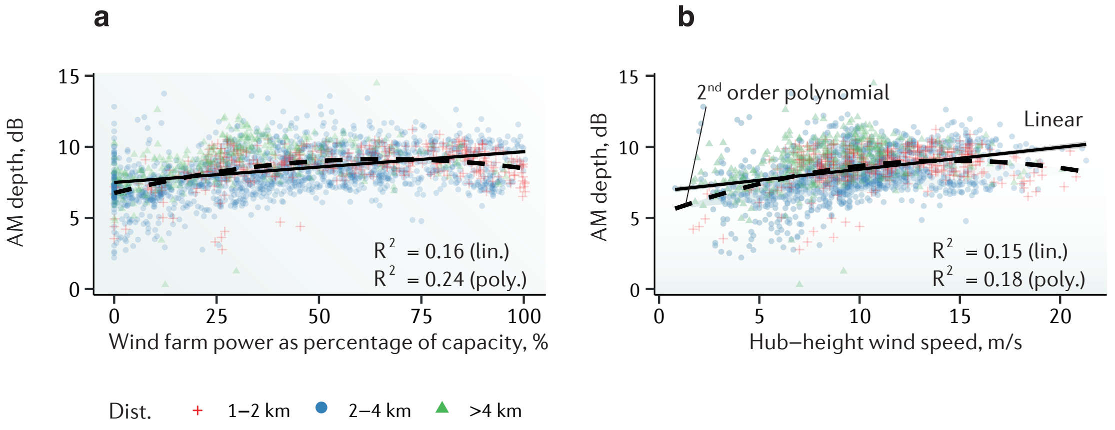


Figure 3.11: Relationship between the AM depth and wind farm power output and the hub-height wind speed.

Tonal AM occurs more often during the night-time (i.e., from 10 pm to 5 am), as shown in Figure 3.12. This finding is consistent with the findings of Van den Berg [3], and it supports the idea that AM is more likely to occur during stable conditions, which occur more often at night-time. Approximately 10% of the total measurement time at night-time contained audible AM. However, at residences located up to 3.5 km from the wind farm, audible AM occurred 22% of the measurement time at night-time.

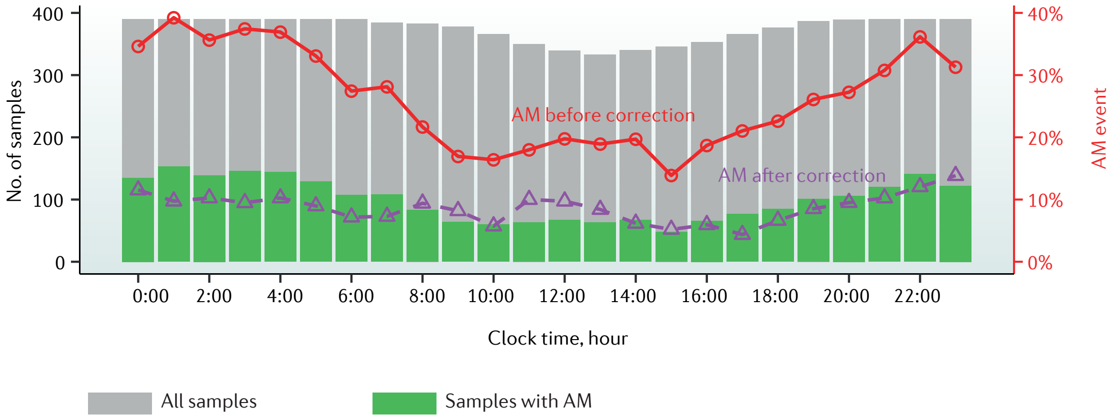


Figure 3.12: Number and percentage of time that AM was present as a function of time of day.

3.5 Discussion

The characteristics of AM depend on meteorological and wind farm operating conditions. To the best of my knowledge, this is the most comprehensive analysis of wind farm AM for noise measured at distances greater than 1 km from a wind farm.

Although the original IOA algorithm is a suitable AM detector (AUC = 0.71), using a prominence factor of four underestimates the number of AM occurrences. This is expected because the IOA method has been developed for detecting broadband AM, while this study aims to characterise low-frequency tonal AM. To improve the performance of the IOA algorithm, I made modifications to the algorithm. The modified IOA method has a better performance (AUC = 0.79) for our data, although this method could potentially be improved to reach higher AUC values.

Although analysis of a larger data set is needed, I found that the AM characteristics at Wind farm 1 differ from Wind farm 2. A possible explanation for the difference in AM depth could be attributed to the use of different sizes of turbines in the wind farms. While Wind farm 2 used Vestas V90-3MW turbines, which have a rotor diameter of 90 m, Wind farm 1 used Suzlon S88-2.1MW turbines with a rotor diameter of 88 m. As a result, the change in the atmospheric wind speed is less for each blade rotation of the wind turbines at Wind farm 1 compared to Wind farm 2. Also, there is a significant difference in the rated power of these turbines. These differences could affect on the AM characteristics such as AM depth and/or AM prevalence.

The indoor AM depth is higher than that outdoors, while the number of AM occurrences for the indoor case are fewer than those for the outdoor case. This could be due to indoor background noise masking the AM signals. The background noise in the 50 Hz 1/3-octave band was higher indoors, resulting in only clear AM events being detected, and thus a shift in the mean value and a lower AM occurrence.

I calculated the percentage of time that AM was present at each house. The results showed that tonal AM is audible both outdoors and indoors up to distances of 3.5 km from the nearest turbine in the wind farm. This is because the attenuation of low-frequency noise is lower than that of higher-frequency noise. This results in relatively large propagation distances for low-frequency tonal AM compared to mid-frequency swishing noise. In fact, AM can be detected up to 8.8 km from the wind farm by the algorithm, although it is inaudible for individuals with normal hearing.

AM is more likely to be detected when the wind turbines are operating below their maximum rated power. It is unclear if this is a source characteristic or if it is an environmental effect, as the background noise may also be higher due to wind noise at the receiver when the wind farm is operating at higher power capacities. This could result in non-detection of AM, even though it may be present. AM also occurs much more frequently during the night-time, which is due to favourable conditions such as low background noise levels and stable atmospheric conditions. Stable atmospheric conditions are characterised by high wind shear, which is suggested to be a major factor responsible for the AM of WFN [3]. Also, an atmospheric temperature inversion (increasing air temperature with increasing altitude) is found during the night-time, which makes WFN louder, especially in downwind conditions.

3.6 Summary

In this chapter, I demonstrated that modifications are necessary to improve the performance of the IOA method for detecting and quantifying low-frequency tonal AM. I showed that AM characteristics are different at different wind farms, although further analysis based on a larger data set is needed to support this finding. I also found that low-frequency tonal AM measured indoors occurs approximately 20% of the time up to a distance of 2.4 km. Despite the fact that the number of AM events are shown to reduce with distance, audible indoor AM still occurred for 16% of the time at a distance of 3.5 km. At distances of 7.6 and 8.8 km, audible AM was only detected on one occasion. At night-time, audible AM occurred indoors at residences located as far as 3.5 km from the wind farm for up to 22% of the time. These findings will serve as an invaluable reference to study possible sleep disruption and noise annoyance that is caused by wind farm AM.

Creativity is intelligence having fun

— Albert Einstein

4

Synthesis and evaluation of amplitude modulation stimuli

Contents

The content of this chapter has been submitted:

1. **Nguyen DP**, Hansen K, Zajamsek B, Catcheside P. Evaluation of wind farm noise amplitude modulation synthesis quality. *Applied Acoustics* . 09/2019 (Q1) [**Under review**]

(The Statement of Contribution forms are provided in Appendix A)

4.1 Introduction

In laboratory listening experiments that study the effects of AM on annoyance and sleep disturbance, AM stimuli are commonly synthesised and can thus suffer from a lack of ecological validity. In this chapter, I evaluate the quality of synthesised amplitude modulation stimuli by comparing five stimuli synthesis methods with measured noise in terms of perceptual quality and spectral similarity. I used an ABX discrimination listening test [34] to evaluate the perceptual quality. I also used a one-third octave band spectra to evaluate the similarity between synthesised and measured noise spectrum. The results of this chapter are used in Chapter 5 where I will investigate the effects of AM on sleep acceptability.

4.2 AM synthesis methods

For the purpose of signal synthesis, tonal AM is assumed to be a combination of WFN without an amplitude modulated tone (hereafter referred to as background noise (BGN)) and an amplitude modulated tone (AT), as follows:

$$AM = \beta \times (AT + \alpha \times BGN) \tag{4.1}$$

where β is a constant for controlling the overall SPL and α is a constant for controlling the level of background noise.

4.2.1 Background noise component

Environmental background noise can be modelled by the power-law ($1/f^{\gamma}$) with a linear relationship between the log power spectral density and the log frequency [22]. The parameter γ can take values between 0 and 2 with characteristic values of 0, 1 and 2 for white, pink and brown noise, respectively. In the present study, BGN was represented using pink noise (Figure 4.1a (upper panel)) because this noise widely occurs in a variety of natural environments [23] and was previously used for synthesising WFN [21]. For example, Yokoyama et al. [7] used the power-law for synthesising BGN with a slope of -4 dB/octave (for comparison, pink noise has a slope of -3 dB/octave).

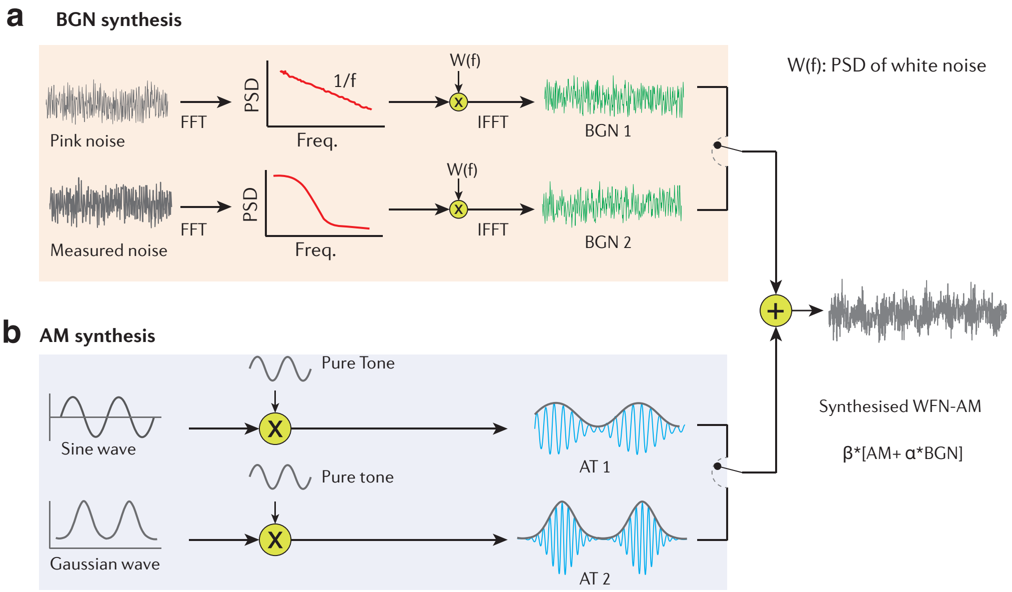


Figure 4.1: Method for synthesising AM stimuli. **a**, Two methods for synthesising BGN using pink-noise (upper panel) and real WFN (lower panel). **b**, Two methods for synthesising an AT component using sine wave (upper panel) and Gaussian pulse train (lower-panel). Modulated signals are multiplied with a 46 Hz tone to create an AT component, which is then added to a BGN to form the tonal AM.

The second method for synthesising BGN is based on measured WFN [6], as shown in Figure 4.1a (lower panel) and Appendix A, which provides the synthesis method details. According to this method, the real noise sample is transformed into the frequency domain after moving average filtering, providing the general noise spectrum. The general spectrum is then multiplied with the white noise spectrum and the product is transformed back into the time domain using the inverse fast Fourier transform (IFFT).

4.2.2 Amplitude modulation component

The AM part is synthesised using either a sine wave or a Gaussian pulse train, as shown in Figure 4.1b. The Gaussian pulse train appears to more accurately represent AM [9] by allowing control over the pulse shape and spacing between the pulses. This is important because the AM pulse can be asymmetrical, depending on the position of the receiver, and the spacing can vary due to propagation effects and changes in the blade rotational frequency. Conversely, while the sine wave does not allow for such detailed tuning, it allegedly provides a satisfactory approximation of the AM [9]. Both methods have been used in previous studies [9, 35].

4.2.3 Synthesis results

The final AM synthesised noise was created by combing the BGN and AT into five unique combinations, as outlined in Table 4.1. All synthesised samples had a 0.8 Hz modulation frequency, and a 46.5 Hz carrier centre frequency, as well as a modulation depth of 8 dB and a tonal audibility of 10 dB. However, to accurately represent the characteristics of measured wind farm AM, the amplitude of AT signals used in Method 4 and 5 was varied randomly so that the modulation depth was 8 ± 2 dB (value is mean ± standard deviation). Also, the shape signals used in Method 5 were designed to have an asymmetric Gaussian shape, which is resemble the shape of the measured AT signals in the time-domain [36].

Table 4.1: AM synthesis methods.

Method	AM	AM characteristics
1	BGN 1 + AT 1	Constant amplitude, sine wave
2	BGN 2 + AT 1	Constant amplitude, sine wave
3	BGN 2 + AT 2	Constant amplitude, symmetric Gaussian wave
4	BGN 2 + AT 2	Random amplitude, symmetric Gaussian wave
5	BGN 2 + AT 2	Random amplitude, asymmetric Gaussian wave

Comparisons in both the frequency and time domain between synthesised and measured noise are shown in Figure 4.2. The one-third octave band spectra from synthesised Method 1 contain some large differences when compared with the real measured AM spectra, while the agreement between Methods 2-5 and the real AM is good (Figure 4.2a). The difference between Method 1 and other Methods is also found in the time domain, as shown in Figure 4.2b.

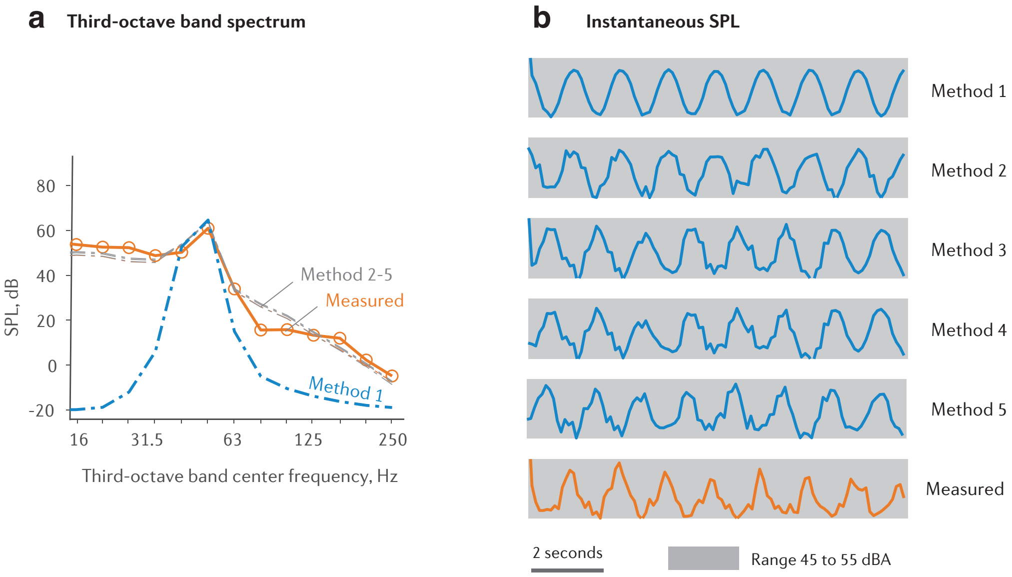


Figure 4.2: Comparison between synthesised and measured noise. **a**, Comparison between the one-third octave band spectra. **b**, Comparison in the time domain. The gray shaded region shows the range of SPL between 45 and 55 dBA.

4.3 Evaluation of the perceptual quality of the stimuli

4.3.1 Participants

Following approval from the Social and Behavioural Research Ethics Committee (SBREC) at Flinders University under project number 7536, 10 participants (5 males) aged from 21 to 50 years old were recruited for the listening test. Eight participants (five acoustic engineers and three psychologists) were familiar with WFN. All participants had normal self-reported hearing.

4.3.2 Testing room and instrumentation

The listening test was conducted in a bedroom at the Adelaide Institute for Sleep Health (AISH), Flinders University, where the daytime background noise level is below 21 dBA. The noise reproduction system consisted of an RME Babyface Pro sound card, Lab Gruppen C 16:4 power amplifier and Krix Harmonix MK2 loudspeaker. The SPL at the participants' ears was 50 dBA, and noise samples were smoothly ramped up and down using a 0.5 s raised-cosine function. The loudspeaker was positioned in front of the participants, and its centre was aligned with the participant's ear level (Figure 4.3b). The listening test was delivered via a MATLAB GUI on a tablet PC with touch control. Figure 4.3a compares the room background noise spectrum and the real WFN-AM spectrum on which the synthesis of BGN 2 is based. The detailed view shows the tonal peak at approximately 46.5 Hz with sideband peaks spaced at the blade pass frequency, which are characteristic features of an AM tone.

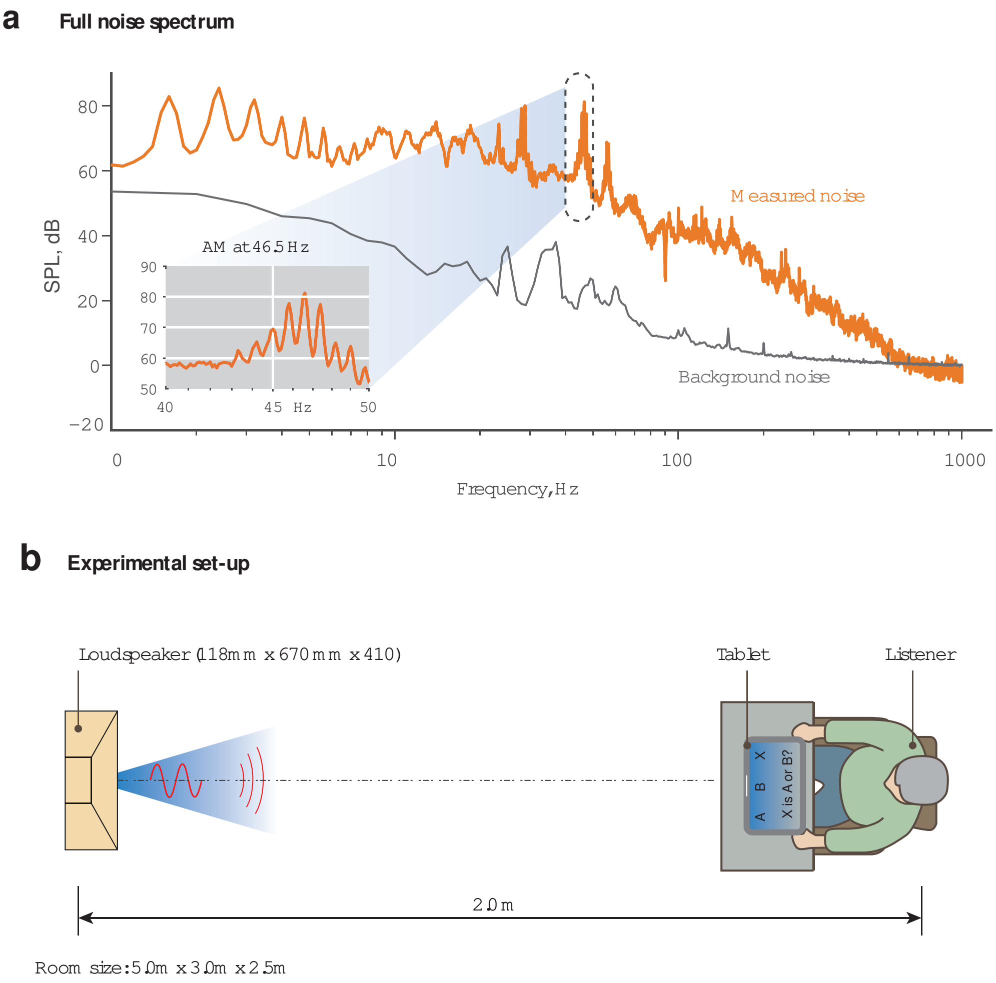


Figure 4.3: Stimuli and experimental design. **a**, The spectrum of measured WFN and background noise. The dashed line window shows a magnified view of the spectrum between 40 and 50 Hz, which the 46.5 Hz tonal AM occurs. **b** Listening test set-up.

4.3.3 Experimental design

An ABX listening test [34] was used to evaluate the perceptual difference between the synthesised and the real AM noise samples. In this test, the participants listened to a pair of noise samples, A and B, in which one was real and one was synthesised. Whichever was real was determined randomly. After hearing noise sample pair A and B, the participants were presented with noise sample X, which was either A or B, and for which the participant had to decide whether X was A or B. Apart from the ABX task, the participants were also asked to rate '*How confident are you about your choice?*' and '*How likely it is that sound A and B belong to the same recording?*' on an 11-point discrete scale from 0 (not at all) to 10 (extremely). The extreme alternatives were labelled as "*Not at all*" and "*Extremely*". Each of the five noise sample pairs were played 10 times, including five presentations of X=A and the other half with X=B. Altogether, each participant was presented with 50 noise pairs, and the test took approximately 20 minutes.

4.3.4 Statistical analysis

All statistical analysis including the one-tailed binomial exact test, one-way analysis of variance (ANOVA) and Tukey pairwise comparisons were performed using R `http://www.r-project.org/`. The significance threshold used was $p = 0.05$.

4.3.5 ABX test results

An exemplary ABX test response matrix using signal detection theory [34, 37] for one noise pair is shown in Table 4.2. In the response matrix, correctly recognising "*X matches A*" is termed a *Hit* and failing to recognise it is termed a $Miss$. Mistakenly recognising "$X = A$" as "$X = B$" is a $False\ alarm$ and responding "B" to "$X = B$" is a $Correct\ rejection$. The number of correct answers is the sum of the hits and correct rejections. For example, the response matrix provided in Table 4.2 has five correct answers. From the response matrix, a hit rate (HR), $HR = \frac{Hit}{Hit+Miss}$, a false alarm rate (FAR), $FAR = \frac{False\ alarm}{False\ alarm+Correct\ rejection}$, and a sensitivity measure $d' = z(HR) - z(FAR)$, where z stands for z-transform, are calculated.

Table 4.2: A typical ABX test response matrix.

Sample sequence	Response, X = A	Response, X = B
X=A	Hit (2)	Miss (3)
X=B	False alarm (2)	Correct rejection (3)

The results of the ABX tests are shown in Figure 4.4a, in which listeners had to distinguish between real and synthesised noise with 50% probability of correct identification by chance. Only samples from method 1 could be distinguished ($p = 0.01$), while samples from other methods were indistinguishable (Figure 4.4b).

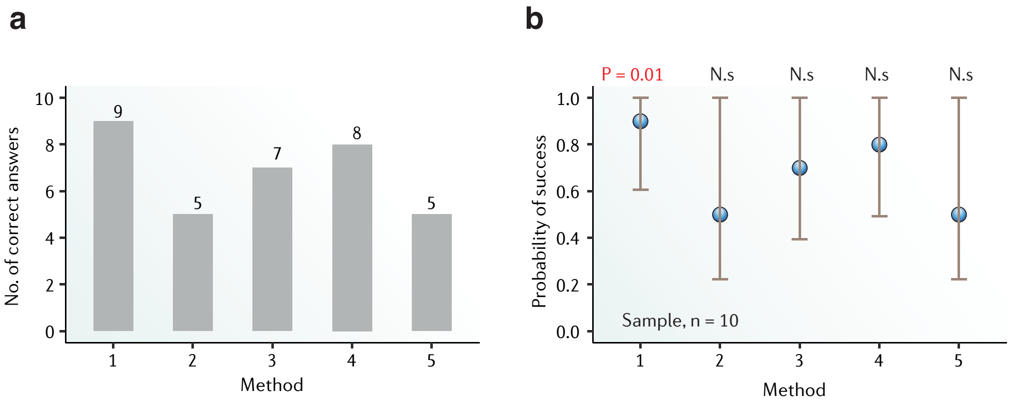


Figure 4.4: ABX test results (n=10) for all five methods. **a**, Number of correct answers out of 10. **b**, Probability of success with one-tailed binomial exact test results where ‘N.s’ stands for non-significance and error bars indicate 95% CI.

Though valid, a binomial test for testing the null hypothesis of ABX results is not optimal due to the small sample size for which signal detection theory (SDT) is more suitable [37]. SDT uses the sensitivity measure, d', to quantify the level of difference between stimuli. The value d' lies between 0, which indicates no difference and 4.65, which is an effective ceiling that indicates a maximal difference between stimuli [34]. It is suggested that a d' larger than 2.5 represents a clearly perceivable difference, whereas a d' of 1 is considered a threshold value below which a participant cannot distinguish between the two types of noise [38]. The results in Figure 4.5b show that only samples synthesised using method 1 were clearly different to the real samples ($d' > 2.5$). This is consistent with the results using a binomial test. Furthermore, samples from methods 2 and 5 were the most difficult to separate, with a d' of 0 (Figure 4.5)b. Methods 3 and 4 are somehow ambiguous and without clear differences between the real and synthesised samples.

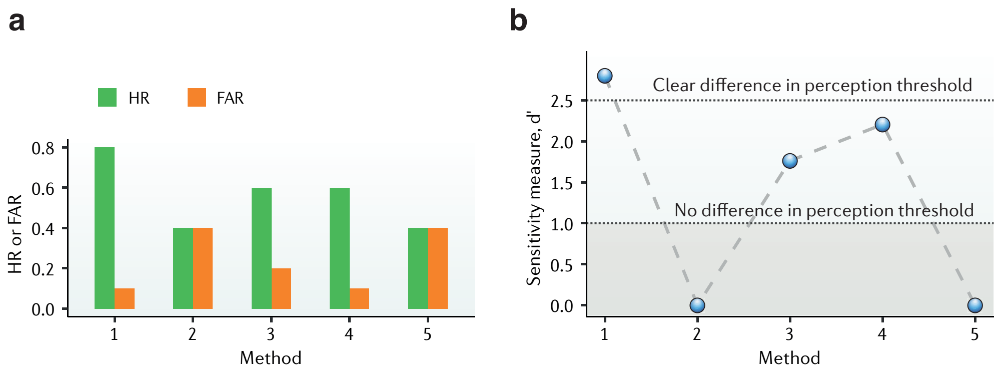


Figure 4.5: Signal detection theory results. **a**, Hit rates (HR) and false alarm rates (FAR) according to signal detection theory (SDT). **b**, Sensitivity measure, d', according to SDT.

4.3.6 Confidence and similarity rating results

The participants were very confident in distinguishing between the real and synthesised noise from method 1, as reflected by the high confidence ratings (Figure 4.6a). There was a significant difference between confidence ratings for the various methods (ANOVA, $p = 0.018$). Although a clear pairwise trend is apparent in Figure 4.6c, with large differences between method 1 and the other methods, only pairs 2-1 and 4-1 were significant. Similar trends were apparent for the similarity rating in Figure 4.6d, with a significant difference between the methods (ANOVA, $p < 0.005$), in which method 1 was clearly different to all the others.

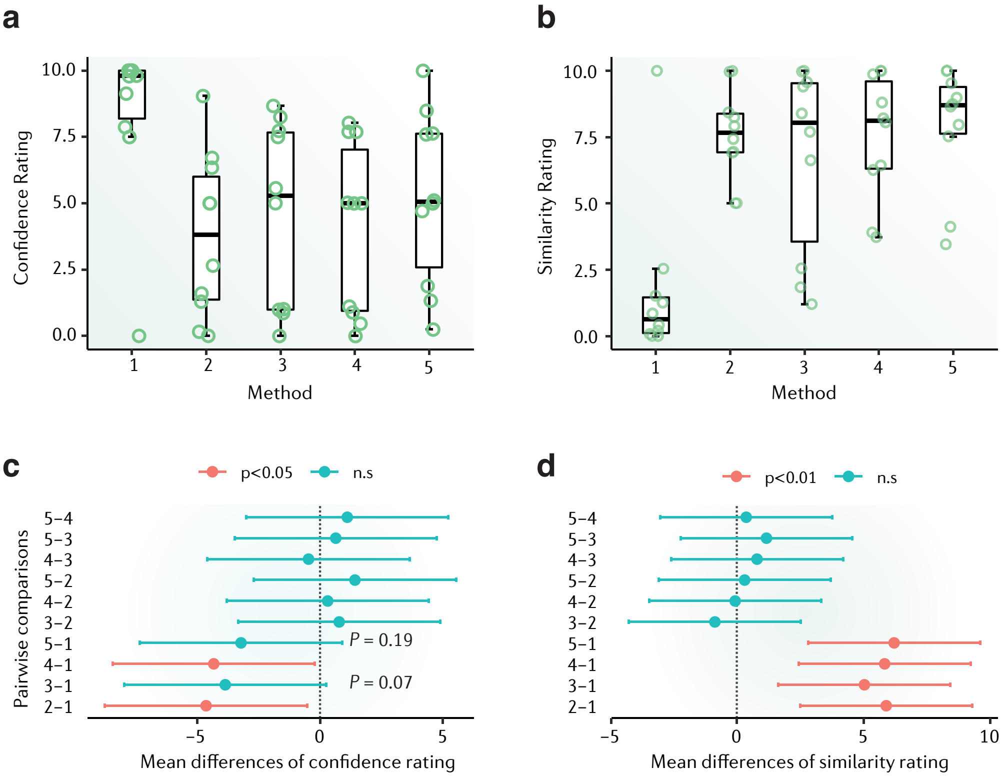


Figure 4.6: **a**, Similarity. **b**, Confidence rating results. **c**, Tukey HSD paired comparison test for confidence. **d**, Tukey HSD paired comparison test for similarity rating results, with error bars indicating 95% CI.

4.4 Discussion

Based on perceptual evaluation and visual inspection tests, I found that synthesised noise provides adequate ecological validity. This suggests that using synthesised stimuli for laboratory experiments is valid and suitable. To the best of my knowledge, this is the first time the quality of synthesised wind farm noise AM has been tested.

I found that the BGN has a significant effect on how the participants perceive the noise. For example, while stimuli synthesised using Method 1 (pink-noise) are clearly different to the measured noise, stimuli synthesised using Method 2 (real WFN) are similar to the measured noise. However, in contrast to the use of BGN, increasing the level of complexity in synthesising AT signals did not improve the quality of the stimuli as shown through the comparison between Methods 2 to 5.

This reveals an important conclusion that the noise spectrum is as equally important as the unique characteristics of the noise (i.e., infrasound, tonality and AM).

To my surprise, using a sine wave for synthesising AT signals has equally good quality as using an asymmetric Gaussian wave that is expected to accurately represent the characteristics of the real noise. A possible explanation is that the difference between using a sine wave and asymmetric Gaussian wave is not substantial enough to make a difference in the perception.

4.5 Summary

In this study, I implemented five methods for synthesising AM, and these synthesised stimuli then were evaluated using an ABX listening test. I found that using background noise based on measured AM is important in producing ecologically valid synthesised AM. Also, I demonstrate that simple synthesis methods are sufficient for good synthesis. Some synthesised AM stimuli were found indistinguishable from measured AM samples by the participants, which shows that synthesised noise can provide adequate ecological validity, along with complete control over the signal parameters, thus making it ideal for laboratory experiments.

No great discovery was ever made
without a bold guess.

— Isaac Newton

5

Effects of amplitude modulated noise on the acceptable noise level for sleep

Contents

Part of the research contained in this chapter has been published as:

1. **Nguyen DP**, Hansen K, Zajamsek B. Wind farm infrasound detectability and its effects on the perception of wind farm noise amplitude modulation. *In Proceedings of ACOUSTICS 2019 Nov 9.* [**Accepted**]

2. Hansen K, **Nguyen DP** , Zajamsek B, Micic G, Catcheside P. Pilot study on perceived sleep acceptability of low-frequency, amplitude modulated tonal noise. *23rd International Congress on Acoustics, Aachen, Germany, 2019*

September 8-13. `http://pub.dega-akustik.de/ICA2019/data/articles/000499.pdf` [**Published**]

(The Statement of Contribution forms are provided in Appendix A)

5.1 Introduction

This chapter investigates the perceived sleep acceptability of WFN containing low-frequency tonal AM through listening tests. The global expansion of wind farm facilities has been associated with community complaints regarding sleep disturbance. This may be related to the presence of AM, which has been shown to result in increased annoyance. However, it is presently unknown whether acceptability for sleep is judged differently to annoyance, or if AM may be more problematic for sleep than other noise types. Previous studies have also focused predominantly on swishing noise rather than on low-frequency tonal AM, where the latter has been more consistently measured at several wind farms in South Australia at distances greater than 1 km.

5.2 Material and methods

5.2.1 Participants

A total of 13 participants aged between 21 and 46, took part in the listening tests. The participants were employees and students at AISH, none of whom have lived near a wind farm. This study was approved by the Flinders University Social and Behavioural Research Ethics Committee (SBREC project 7536). All participants provided voluntary informed written consent.

5.2.2 Testing room, instrumentation and stimuli

Experiments were conducted in a bedroom located in the AISH Nick Antic Sleep Laboratory. The background SPL of the room was 21 dB(A). Participants were instructed to lie flat on a bed and to relax while they were presented with a total of 13 stimuli. The stimuli were five-minutes long and were played via Bose Quiet

Comfort II headphones. Headphones were used to enable a faithful reproduction of the signals and to minimise ventilation noise contamination at low frequencies. The noise signals were created with MATLAB and reproduced via an RME Babyface Pro sound card, which has a flat frequency response within 0.5 dB, from 0 Hz to 20.8 kHz. The headphones were calibrated using the HEAD acoustics HMS III artificial head and the frequency content was adjusted to match the original signal.

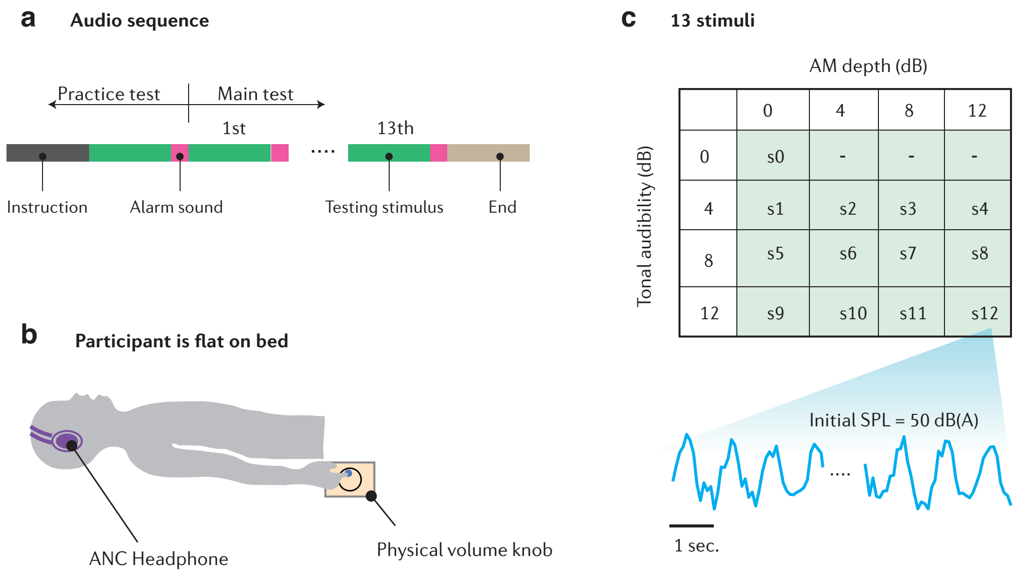
5.2.3 Experimental procedure

The listening test was designed using pre-recorded audio instructions and an inter-stimulus alarm that was kept constant for each participant to minimise possible biases. A representation of the test procedure is provided in Figure 5.1a. The noise samples were presented in random order to account for systematic error associated with carry over effects and sensitisation/de-sensitisation to noise. Each participant underwent a practice test to ensure familiarity with the testing procedures and requirements. The experimenter remained in the room for this phase of the test to answer any questions from participants.

Participants were instructed to lie on a bed and relax for the duration of the test. Lights were turned down to less than 1 lux when the experimenter exited the bedroom and the experimental trial formally commenced. Participants wore Bose Quiet Comfort II headphones and the Active Noise Control (ANC) feature was switched on to minimise background noise contamination. They were provided with a physical volume control knob that was used to adjust the SPL of noise to the maximum level the participant considered acceptable for sleep. The test arrangement is depicted in Figure 5.1b. Visual volume cues were not displayed on the control knob, thus adjustment relied solely on auditory input from the headphones.

A total of 13 noise samples were presented at various combinations of tonal audibility and AM depth for the 50 Hz tone under investigation, as shown in Figure 5.1c, with sample s0 representing the baseline. The total test time was approximately 70 minutes, including instructions.

For each participant, the noise presentation began at a relatively high level of 50 dB(A), with the intention that the majority of participants would wish to reduce the SPL for sleep acceptability. The SPL adjustment was recorded using the sound card software, which provides a loopback function. This allowed real-time signal information to be sent to MATLAB for later post-processing. Participants could adjust the SPL between a minimum of no noise signal and a maximum SPL of 70 dB(A).



	0	4	8	12
0	s0	-	-	-
4	s1	s2	s3	s4
8	s5	s6	s7	s8
12	s9	s10	s11	s12

Figure 5.1: Experimental set-up.

5.3 Results

5.3.1 Adjustment time for tonal AM acceptability for sleep

Adjustment time is the period starting from when the sound started playing until a participant's final adjustment. To find the adjustment time for a participant, the SPL adjustment is plotted against time, as shown in Figure 5.2a. The time at which the adjustment was less than 1 dB over five seconds was considered as the final adjustment. One dB is considered as a typical fluctuation of the room background noise rather than the adjustment. The adjustment time was calculated for each sample and each participant. In total, 169 adjustment times (13 samples x 13 participants) were recorded to construct the probability density function

(PDF) as shown in Figure 5.2b. I found that most participants needed less than 60 seconds to find their acceptable level of noise for sleep while, some participants still needed up to 280 seconds. Therefore, to find a reasonable adjustment time which could satisfy the majority of participants, I constructed a cumulative distribution function (CDF) (Figure 5.2b). I found that a sample length of 210 seconds could satisfy 95% of the participants. However, closer inspection of the plot indicated that as the slope of the CDF is small, the sample length could be reduced to 180 seconds and participants would still be satisfied for 94% of the time. Therefore, I propose that an adjustment time of 180 seconds is reasonable for future listening tests involving similar noise samples.

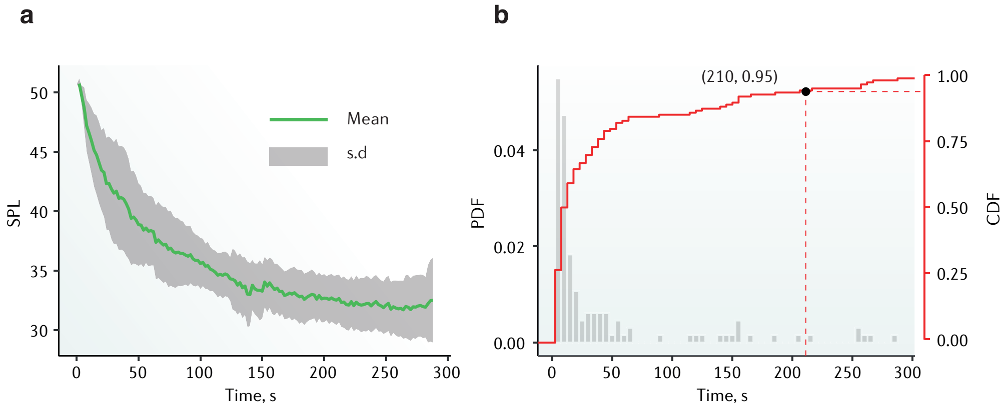


Figure 5.2: Adjustment time for tonal AM acceptability for sleep. **a**, Mean and standard deviation of the sound pressure level (SPL) adjustment as a function of time. **b**, Probability density function (PDF) and cumulative distribution function (CDF) of the time taken for the final adjustment of all samples/participants. The black dot represents the adjustment time that would be satisfactory for 95% of time.

5.3.2 Noise sensitivity score

Noise-sensitivity scores were calculated based on the 21-item Weinstein Noise-Sensitivity Scale [39]. The sensitivity scores of 13 participants are shown in Figure 5.3a, in which a higher score denotes higher sensitivity to noise. The sensitivity scores are followed a normal distribution based on visual inspection using Q-Q plot. To separate the participants into two groups (i.e., insensitive and sensitive group), I calculated the group mean noise-sensitivity score, which is 61 ± 17 (values are mean ± s.d. throughout). Participants who scored higher than 61 points were considered noise sensitive participants and participants scoring lower were considered noise insensitive. In addition, to examine whether the noise sensitivity score affects the final SPL adjustment, I found that this relationship was strong ($R^2 = 0.44$, $p = 0.008$), as shown in Figure 5.3b.

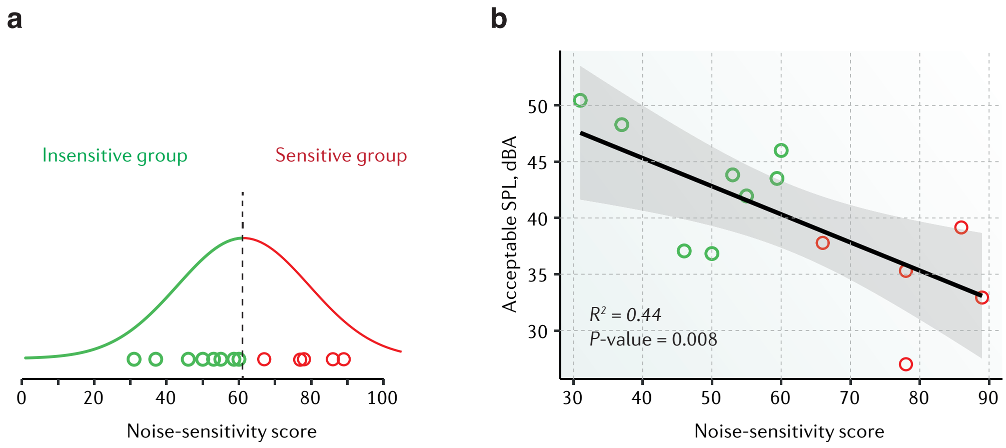


Figure 5.3: Noise sensitivity score. **a**, Noise sensitivity scores and the associated normal distribution and classification of noise-sensitive and insensitive groups. **b**, Relationship between overall acceptable SPL for sleep and the noise-sensitivity score. A linear regression fit is shown using the solid black line and the 95% CI indicated by the gray shaded region.

5.3.3 Sleep acceptability of tonal AM

The relationship between tonal audibility, AM depth and SPL difference is shown in Figure 5.4. The y-axis values represent the difference between the final SPL adjustment for the baseline noise sample and the samples with tonal AM. A negative value indicates that a penalty may be necessary to ensure that WFN is acceptable for sleep. The noise non-sensitive group were not affected by tonal AM whereby their acceptable levels for sleep were similar for all samples, as shown in Figure 5.4.

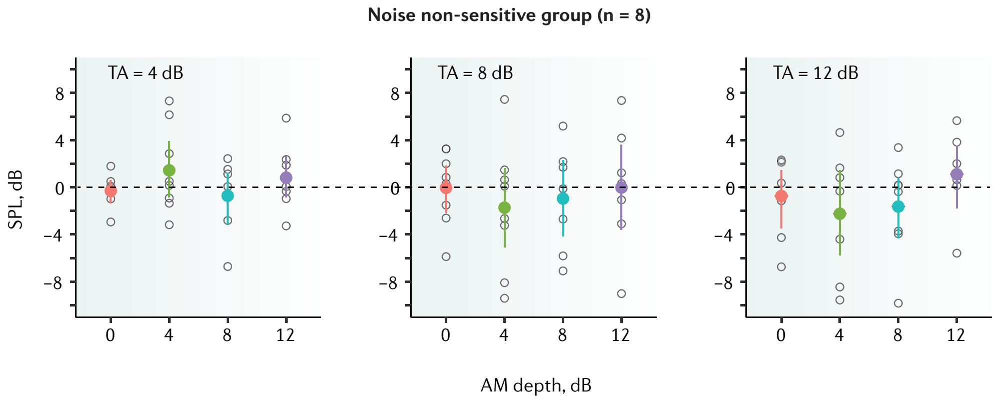


Figure 5.4: Final SPL adjustment relative to the baseline for noise-insensitive participants, n=8.

However, in contrast to the non-sensitive group, a clear trend between tonal audibility and AM depth was evident for the case, in which the tonal audibility was 12 dB(A) and participants were classified as noise-sensitive, as shown in Figure 5.5. The results are consistent with previous studies showing an increased annoyance with increased AM depth [6, 8, 10, 24]. This finding is applicable to about 40% of the sample and suggests that a penalty of up to 5 dB(A) may be required, depending on the AM depth.

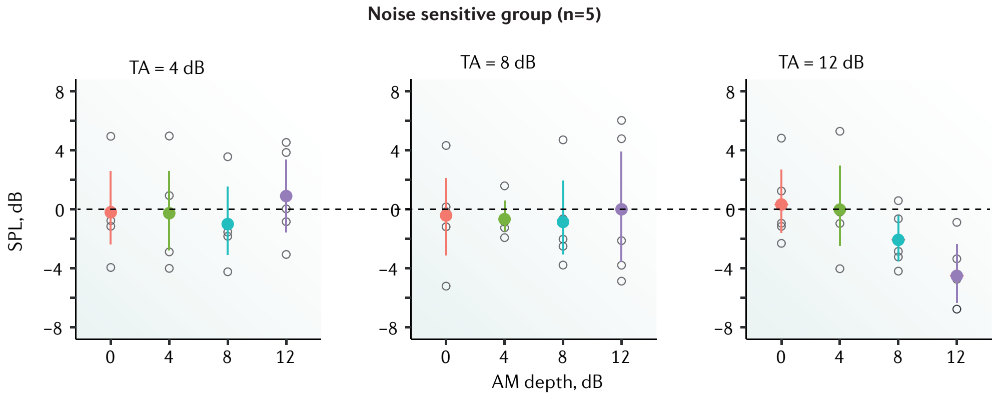


Figure 5.5: Final SPL adjustment relative to the baseline for noise-sensitive participants, n=5.

5.4 Discussion

I found that the 50 Hz tone had minimal impact on sleep acceptability for all values of tonal audibility in the absence of AM. This finding is consistent to the work of Oliva et al [40], who showed that no penalty is be required for low-frequency tonal noise at 50 Hz with tonal audibility between 5 and 25 dB(A). In fact, these researchers found a statistically significant negative penalty value for a tonal frequency of 50 Hz and tonal audibility of 18 dB(A), when the overall LAeq was 25 dB(A). This suggests a reduction in annoyance at low SPLs in the presence of a low-frequency 50 Hz tone.

In this study, I found that some participants found WFN more acceptable for sleep when a 50 Hz tone was present, even when it was amplitude modulated. However, this may be related to the choice of baseline noise sample on which the spectrum shape was based on measured WFN. Perhaps a better choice of baseline noise sample would be one that is based on a room criteria (RC) spectrum shape, which is less objectionable [41].

5.5 Summary

I demonstrated that the perceived acceptable level of WFN for sleep varies between individuals and is inversely proportional with self-declared noise sensitivity. Although studies on larger sample sizes are needed, my results showed that noise-sensitive individuals judged WFN containing tonal AM to be less acceptable for sleep when the tonal audibility was 12 dB(A). For the worst-case noise stimulus, which contained a 50 Hz tone with tonal audibility of 12 dB(A) and an AM depth of 12 dB(A), a penalty in the order of 5 dB(A) may be required. I also found that a stimulus time of three minutes may be a conservative choice for future experiments, given that this satisfied the study sample for 94% of the time.

Research is a road on which one may take many wrong turns before a productive direction is found.

— Nature Methods-Should scientists tell stories?

6

Conclusions and recommendations for future work

For this Master's project, I successfully characterised the AM of wind farm noise measured at several locations in South Australian wind farms. To analyse data measured at large distances from the wind farms, I proposed a modified version of the IOA algorithm which showed better performance than the original IOA algorithm on our data. Also, to prepare AM stimuli for the laboratory experiments, I evaluated the quality of synthesised stimuli based on both visual and perceptual tests. Finally, I tested the effects of AM on acceptable noise levels for sleep based on a pilot study conducted internally. These results improved our understanding of wind farm noise AM and its acceptability for sleep.

I found that AM characteristics are different between wind farms. The results also showed that low frequency tonal AM is audible both outdoors and indoors, up to distances of 3.5 km from the nearest turbine in the wind farm. The modified algorithm can detect AM up to 8.8 km from the wind farm, although it is inaudible for a person with normal hearing. My data showed that AM is more likely to be detected when the wind turbines are operating below their maximum rated power. Also, AM occurs much more frequently during the night-time due to favourable conditions such as low background noise levels and a stable atmosphere.

I found that synthesised noise stimuli can have ecological validity and are suitable for laboratory experiments. Interestingly, although some synthesis methods are relatively simple and required relatively few input parameters, they were indistinguishable from measured AM samples.

Participants responses were highly variable, but in self-reported noise-sensitive individuals, an increase in the AM depth at a tonal audibility of 12 dB was associated with a lower acceptability for sleep. I also found that a stimulus time of three minutes is a good conservative choice for future experiments to ensure that participants are given adequate time to judge acceptability for sleep.

Further research is needed to determine the prevalence of AM on an annual basis. Specifically, the noise data should be measured for at least one year, so that the seasonal and diurnal characteristics of AM can be captured. Further work is also needed to quantify the annoyance and sleep disturbance potential of low frequency tonal AM, particularly with larger sample sizes containing noise-sensitive individuals who have experienced living wind farm noise. This will provide further insight into the relationship between noise sensitivity and WFN disturbance potential as well as shedding light on possible sensitisation to WFN.

Appendices

Publication 1:

Nguyen, D.P., Hansen, K. and Zajamsek, B., 2019. Human perception of wind farm vibration. *Journal of Low Frequency Noise, Vibration and Active Control*, p.1461348419837115. DOI: https://doi.org/10.1177/1461348419837115

Contribution of Each Author:

PN analysed data and wrote the initial manuscript with support from KH and BZ.
KH and BZ carried out the experiment, collected data and contributed final manuscript.
KH and BZ provided critical feedback and helped shape the research, analysis and manuscript. All authors discussed the results and contributed to the final manuscript.

Publication 2:

Hansen, K.L., **Nguyen, P.,** Zajamšek, B., Catcheside, P. and Hansen, C.H., 2019. Prevalence of wind farm amplitude modulation at long-range residential locations. *Journal of Sound and Vibration*, *455*, pp.136-149.
DOI: https://doi.org/10.1016/j.jsv.2019.05.008

Contribution of Each Author:

KH devised the project, the main conceptual ideas, proof outline and wrote the manuscript.

PN analysed the data and shared conceptual ideas and contributed to initial and final manuscript.
KH and BZ designed and collected data.
PC and CH contribute to final manuscript.

All authors discussed the results and contributed to the final manuscript.

Publication 3:

Nguyen, D.P., Hansen, K. and Zajamsek, B., 2018, November. Characterizing tonal amplitude modulation of wind farm noise. In *Proceedings of ACOUSTICS* (Vol. 7, No. 9).

https://www.acoustics.asn.au/conference_proceedings/AAS2018/papers/p101.pdf

Contribution of Each Author:

PN analysed the data and wrote the initial manuscript.
KH and BZ collected data and provided critical feedback and helped shape the research.
All authors contributed to the final manuscript.

Publication 4:

Hansen, K., **Nguyen, D.P.,** Zajamsek, B., Micic G., and Catcheside P., 2019. Pilot study on sleep acceptability of low-frequency, amplitude modulated tonal noise. In *Proceedings of the 23rd International Congress on Acoustics 9-13 September 2019 in Aachen, Germany.*

Contribution of Each Author:

KH contributed the main conceptual ideas and wrote the manuscript.

PN collected and analysed the data, designed the experiment and contributed to main conceptual idea.

BZ, GM and PC provided critical feedback and helped shape the research.

All authors contributed to the final manuscript.

Publication 5:

Nguyen, D.P, Hansen, K., Zajamsek, B., Micic G., and Catcheside P., 2019, November. Wind farm infrasound detectability and its effects on the perception of wind farm noise amplitude modulation. In *Proceedings of Acoustics 2019 Melbourne, Australia.*

Contribution of Each Author:

PN designed the experiment, collected and analysed data and wrote the manuscript.

PN, BZ and KH contributed the conceptual ideas.

BZ, GM and PC provided critical feedback and helped shape the research.

All authors contributed to the final manuscript.

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