

Long-term investigation into wind farm amplitude modulation and annoyance

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ABSTRACT

Despite widespread community acceptance of renewable power generation to reduce CO₂ emissions and natural resource impacts, large-scale expansion of wind farms has prompted significant community debate regarding adverse health impacts of wind farm noise (WFN). Our research has aimed to investigate this issue by identifying, quantifying, and characterising the components of WFN that are responsible for annoyance and sleep disturbance. In this study, we carried out 1-year-long acoustic and meteorological measurements at three residences located near different wind farms, allowing detailed characterisation of WFN and its relationship with meteorological conditions. At two of these residences, participants recorded their subjective annoyance, providing insight into the relationship between specific noise features and human response. To detect amplitude modulation (AM), which is a particularly annoying component of WFN, we used a novel detection algorithm which significantly outperformed previous methods. Application of this algorithm revealed that AM prevalence was 2 to 5 times higher during the nighttime compared to the daytime. Annoyance due to WFN was reported most often during the nighttime and early morning, consistent with the measured AM prevalence. Participants most often described the noise as a "swish" or "swoosh" and the presence of these signal components was confirmed via spectral analysis.

1 INTRODUCTION

Wind is one of the world's fastest-growing renewable energy sources (Global Wind Energy Council (GWEC), 2019), reaching approximately 870 GW in 2021 ((WindPower, 2021). This rapid expansion of wind farms has been accompanied by concerns regarding adverse noise impacts, including sleep disturbance (Bakker et al., 2012; Nissenbaum, Aramini, & Hanning, 2012), daytime sleepiness (Nissenbaum et al., 2012), psychological distress (Bakker et al., 2012) and reduced health-related quality of life (Shepherd & Billington, 2011). Some argue that these concerns are unfounded and reflect nocebo effects triggered by social discourse and media reports (Crichton & Petrie, 2015). This may be further confounded by multiple factors not directly related to WFN that may still contribute to perceived disturbance from WFN, including living environment (Eja Pedersen & Larsman, 2008), noise sensitivity (Miedema & Vos, 2003), economic benefits (E. Pedersen, Van den Berg, Bakker, & Bouma, 2009), visual effects (Schäffer, Pieren, Hayek, Biver, & Grêt-Regamey, 2019) and attitudes towards wind farms (Eja Pedersen & Waye, 2004). On the other hand, some residents living near a wind farm have abandoned their properties at significant personal and financial cost (Krogh, 2011), while others have implemented expensive sound insulation measures (Botelho, Arezes, Bernardo, Dias, & Pinto, 2017), illustrating the high value that individuals place on peaceful surroundings. Thus, despite the influence of many confounding factors, it is likely that some individuals are adversely impacted by WFN, although the extent of this issue is hitherto unknown.

Noise annoyance is a key driver of adverse noise effects and is well-established for traffic-related noise (Babisch, Ising, & Gallacher, 2003), and increasingly for WFN, which also has noise features that may exacerbate annoyance (Eja Pedersen & Waye, 2004) and increase loudness (Jurado, Gordillo, & Moore, 2019). These features include low-frequency spectral dominance (Ingielewicz & Zagubień, 2014; Zajamšek, Doolan, Hansen, & Hansen, 2016), amplitude modulation (AM), tonality, and substantial contrast between operational versus ambient noise, particularly at nighttime, in the normally quiet rural environments where Australian wind farms are usually located (K. Hansen, Zajamšek, & Hansen, 2014). Although the unique features of WFN are well-known, the relationship between WFN features and noise annoyance in real-world field settings remains largely unknown (Freiberg, Schefter, Girbig, Murta, & Seidler, 2019). Current evidence is limited to population-based studies (Kuwano, Yano, Kageyama, Sueoka, & Tachibana, 2014) that relied on modelling to determine sound pressure levels (SPLs), and listening test studies (K. Hansen et al., 2019; Kristy Lee Hansen, Nguyen, Zajamsek, Micic, & Catcheside, 2019; Schäffer et al., 2016), that have investigated few noise stimuli with limited noise features and unrealistically short exposure times (≤ 5 min.) resulting in limited ecological validity. Very few studies have investigated the impact of WFN on sleep (Jalali et al., 2016; D. Michaud et al., 2016; Smith et al., 2020) and none to date, have been designed to test for temporal relationships between specific WFN features and sleep disturbance. Thus, from the limited evidence available, it is impossible to establish the extent to which prominent WFN acoustic features influence WFN annoyance and sleep disturbance for residents living near wind farms.



Among WFN characteristics, amplitude modulation (AM) is of particular research interest due to its propensity to contribute to annoyance (loannidou, Santurette, & Jeong, 2016; Lee, Kim, Choi, & Lee, 2011; Schäffer et al., 2016) and possible sleep disturbance (Liebich et al., 2021; Micic et al., 2018; Smith et al., 2020). AM in the context of WFN is defined as a periodic variation in SPL at the blade-pass frequency (Bass et al., 2016; C. H. Hansen, Doolan, & Hansen, 2017), typically between 0.4 and 2 Hz, which is commonly described as "swish swoosh" or "rumble". AM typically occurs during the evening and nighttime when environmental conditions tend to be more stable and thus, favourable for AM (Conrady, Bolin, Sjöblom, & Rutgersson, 2020; Kristy L Hansen, Nguyen, Zajamšek, Catcheside, & Hansen, 2019; Larsson & Öhlund, 2014). AM is a highly variable phenomenon which depends on meteorological conditions (Conrady et al., 2020; Larsson & Öhlund, 2014; Paulraj & Välisuo, 2017), distance from the wind farm and wind farm operating conditions (Kristy L Hansen et al., 2019). The associated variations in the AM characteristics make AM challenging to detect using automated techniques. Subsequently, identifying and quantifying AM is also challenging as it depends on the performance of AM detectors.

Previous long-term field studies have investigated wind farm AM and its relationship with atmospheric and wind farm operating conditions to a limited extent. The results showed that wind farm AM was associated with wind direction (Larsson & Öhlund, 2014; Paulraj & Välisuo, 2017) sound speed gradient, solar elevation angle, turbulence intensity (Conrady et al., 2020; Larsson & Öhlund, 2014), and diurnal meteorological variations (Conrady et al., 2020; Kristy L Hansen et al., 2019). The majority of these studies were carried out in cold climates with snow covered ground during the winter months. Snow covered ground has a high sound absorption coefficient, even at low frequencies, and thus attenuates noise much more effectively than other ground surface types (Bies, Hansen, & Howard, 2017; C. H. Hansen et al., 2017; Ostashev & Wilson, 2016). Previous long-term studies (Conrady et al., 2020; Larsson & Öhlund, 2014) recorded only low time and frequency resolutions of acoustic data such as 1/3-octave band or fast time-weighted SPLs which limited analyses to conventional AM detection methods (Bass et al., 2016; Larsson & Öhlund, 2014) unable to reliably detect AM (Nguyen, Hansen, Lechat, et al., 2021). Longterm quantification of AM has been predominantly carried out at distances of 1 km or less from wind farms, where WFN is dominated by mid to high frequencies (> 200 Hz). At larger wind farm setback distances, more typical for Australia, WFN is dominated by lower frequencies (< 200 Hz) (Kristy L Hansen et al., 2019). However, previous studies have not systematically investigated long-term low-frequency AM. Furthermore, although indoor noise is more relevant to annoyance and sleep disturbance than outdoor noise, previous studies have not attempted longterm characterisation and quantification of indoor AM, particularly at long-range distances to a wind farm. Hence, only a few studies have attempted long-term wind farm measurements to date and therefore the prevalence and characteristics of outdoor and indoor AM for a range of setback distances and climates remains unknown.

Few studies have examined the human response to WFN in a real-world field setting. In fact, only two small studies have taken simultaneous noise diary and WFN measurements at residences located near wind farms. A 20-day long study by Jennings and Kennedy (2019) found, via visual inspection of noise diaries, a correlation between subjective reports of wind farm AM and AM quantified using the Institute of Acoustics 'Reference method' (Bass et al., 2016). AM was subjectively described as "swishing" or "swooshing". The dominant frequency range over which AM occurred was 200-800 Hz with AM depths between 2.5 and 6.5 dB at times when annoyance was recorded by residents. A similar study by Janhunen et al. (2017) was carried out over 2-3 weeks during winter and spring and involved 21 participants living between 706 and 2392 m from the nearest wind turbine. Noise measurements were taken at five locations near two different wind farms located in areas with different back-ground noise characteristics. This study focused on audibility rather than annoyance and participants were asked to record indoor WFN audibility on a scale of 0 (no sound) to 3 (very loud). The study showed that WFN was audible indoors between 0 to 14.6% of the time and that WFN audibility appeared to be dependent on location specific background noise, but with no clear relationship between WFN SPL and audibility. In addition to small sample sizes and short monitoring periods, neither study recorded subjective annoyance ratings or indoor noise, so the potential contribution of specific WFN components to annoyance in a field-based setting remains unclear.

The aim of this study was to investigate the relationship between WFN, its AM, and annoyance using one year of continuous outdoor and indoor field measurements. To facilitate automated detection of AM in this long-term dataset, an algorithm was developed, based on machine learning, which significantly outperformed previous AM detection methods. The long analysis period was used to examine seasonal variations in WFN and background noise, to assess the frequency of annoyance over a prolonged time frame and to examine whether annoyance is more likely to occur at specific times during the day or night. This study also sought to determine the strength of relationships between relevant acoustic metrics and annoyance associated with wind farm noise. In addition to acoustic variables, possible relationships between non-acoustic variables such as wind farm power output and meteorological conditions and annoyance were also explored.



2 METHODS

This section describes the measurement set-up and instrumentation as well as providing details on the development of an AM detection algorithm. A description of the participants and recruitment strategy is included, along with details on the noise diary used to collect self-reported data in the field. A description of data analysis techniques and statistical methods is also provided.

2.1 Overview of study region and data collection

The acoustical data sets used in this study contained WFN measured at three residences (H1-H3) located between 980 m and 3.5 km from the nearest wind turbine of South Australian wind farms (Figure 1). An additional residence, H4, was unoccupied and located approximately 30 km from the nearest wind farm, and thus it was assumed that AM WFN did not exist at this location. Noise data were measured for one year at locations H1, H2 and H3 and five months at location H4. The H3 data set also contained approximately three days of measurements of background noise when the wind farm was not operating. At the time of measurements, Wind farms 1, 2 and 3 comprised 99 Siemens 3.2 MW turbines, 70 Suzlon 2.1 MW wind turbines and 37 Vestas V90-3.0 MW wind turbines, respectively.

A typical measurement setup included a microphone that was positioned at 1.5 m above ground level (except H1 where a ground level microphone was used) and protected using a spherical secondary windshield with a diameter of 450 mm (See K. Hansen et al. (2014) for details). The microphone was typically positioned at least 10 m away from the residence and surrounding vegetation to minimize façade reflections and wind-induced vegetation noise. At all measurement locations, acoustic data were acquired using a Bruel and Kajer LAN-XI Type 3050 data acquisition system with a sampling rate of 8,192 Hz and a G.R.A.S type 40 AZ microphone with a 26CG preamplifier, which has a noise floor of 16 dB(A) and a flat frequency response down to 0.5 Hz. Further details of the experimental setup are described in previous work (K. Hansen et al., 2014; Kristy L Hansen et al., 2019).



Figure 1. Measurement locations and experimental set-up. **A**, wind farm layouts and measurement locations. **B** and **C**, typical outdoor and indoor microphone position set-up.

2.2 AM detection algorithm

A machine learning-based random forest method was used for detecting AM (Nguyen, Hansen, Lechat, et al., 2021). A random forest classifier (Breiman, 2001) consists of decision trees, which represent possible outcome



maps for a series of related choices. The decision trees were constructed using randomly selected noise features that were considered as being relevant for WFN AM detection. A comprehensive range of 31 noise features were used and included A-, C-, and G-weighted SPLs, spectral shape, spectral balance, tonality and signal periodicity at the blade-pass frequency. These features can be divided into four categories, including frequency domain features, overall noise features, time domain features and features extracted from the other automated AM detection methods. To classify an input sample (i.e., AM or no AM), the relevant audio features were inserted into every predictor (tree) in the classifier and a majority voting approach was used. The ratio between the number of trees voting "AM" out of the total tree population represented the probability of AM being present. This method allowed for an accurate determination of "AM prevalence", which is the percentage of time that AM was present in 10-sec blocks during each annoyance period.

The model was validated using a benchmark data set which was generated by an acoustic engineer who listened to 6,000 10-sec audio samples. These samples were randomly extracted from the year-long acoustic dataset and they were classified as either containing "AM" or "no AM". The area under the precision recall curve and the false positive rate were used to evaluate the detection accuracy and the results were compared to three previously published AM detection methods. The first method, labelled a1 (Bass et al., 2016), uses a "hybrid" approach involving analysis in both the time- and frequency-domains. The other two methods labelled a2 (Larsson & Öhlund, 2014) and a3 (Fukushima et al., 2013) are implemented in the frequency- and time-domains, respectively.

2.3 Participants and self-reported data collection

To be eligible for the study, one occupant at each residence needed to confirm that they were disturbed by wind farm noise and this participant was responsible for recording their annoyance via noise a diary. Participants also needed to agree to host instrumentation inside and outside of their residence for the 1-year study duration. To recruit participants, the study was advertised via 585 postal flyers, four community talks and word-of-mouth. Despite the extensive advertising conducted, only four participants decided to take part in the study. These four participants provided voluntary informed written consent and received \$500 reimbursement for study involvement. During monthly instrumentation checks, the participants were asked whether they had completed any noise diary entries and subsequently, relevant pages were collected to minimise potential data loss. Despite this, only two residents were able to complete a sufficient number of noise diary entries for meaningful analysis and hence results from only two locations are reported. These residences are located in remote rural areas, where the back-ground noise is minimal and can be generally attributed to occasional farming activities, local traffic and wind noise. The participants at these two locations were both male and were aged 44 and 54 at the time of study consent. This study was approved by the Flinders University Social and Behavioural Research Ethics Committee (SBREC project 7536).

Participants were provided with a pen-paper noise diary template (see Supplementary in Kristy L Hansen et al. (2021)) and asked to record whether or not they were disturbed by wind farm noise over the 1-year study duration. They received verbal instructions on how to fill in the noise diary when the instrumentation was installed in their homes. To make a diary entry, participants were asked to record the start and end time of their rating, rate their level of annoyance using a 5-point scale (1 Not at all; 2 Slightly; 3 Moderately; 4 Very; 5 Extremely) (ISO TS 15666, 2003), describe the noise character and indicate whether the disturbance was heard or perceived via means other than hearing or both. The annoyance responses were collapsed as per ISO TS 15666 (2003) and consistent with previous research (D. S. Michaud et al., 2016; E. Pedersen et al., 2009) whereby participants reporting to be either "very" or "extremely" annoyed were classified as "highly annoyed" and participants reporting to be "not at all", "slightly" or "moderately" annoyed were treated as "not highly annoyed".

2.4 Data and statistical analysis

The present study analysed the outdoor WFN noise data measured at 1.5 m above ground level (except at H1 where noise was measured at ground level) and indoor data measured in a top room corner. To maximise data quality, an L_{Aeq} plot of all data against time was constructed, and extraneous noise events were detected visually and manually excluded if noise contamination was confirmed through listening to the audio file. Less than 10% of the total measured samples were excluded (See (Nguyen, Hansen, Catcheside, Hansen, & Zajamsek, 2021)). All signal processing and data analysis was implemented in MATLAB (https://www.mathworks.com), while statistical analysis (two-tailed t-test and linear regression, as appropriate) was implemented in R version 4.0.0 (https://www.r-project.org). The statistical significance threshold was set at p < 0.05.



3 RESULTS

3.1 AM detection algorithm performance

The performance of the random forest-based AM detection method is compared to three automated detectors (a1-a3) on precision-recall plots in Figure 2 The test set for detectors a1-a3 included all samples in the benchmark data set, while the test set for the random forest detector included all data not used for model training (out-of-bag samples). The random forest-based method outperformed the other methods (ANOVA p-value < 0.001), with an AUPRC of 0.85 (where 1 represents 100% detection of AM). In fact, the algorithm performance was found to be comparable to human performance, based on inter-scorer agreement (Nguyen, Hansen, Lechat, et al., 2021). Furthermore, this AM detection method substantially outperformed previous AM detection algorithms, where the mean AUPRC for a1-a3 ranged from 0.43 to 0.55. The performance of a1 was better than a2 and a3 (all p < 0.001), and a2 performed better than a3 (p < 0.001).



Figure 2. Performance of automated detectors. A, performance using the benchmark data set, where the values associated with each curve are mean [95% confidence interval]. The shaded area is the 95% CI. B, false positive rate of each detection method estimated from the no wind farm noise data set. The dashed lines indicate the AM classification threshold.

The performance of AM detection algorithms has previously been described in terms of the false positive rate (FPR) (Bass et al., 2016; Larsson & Öhlund, 2014), and thus this metric was also examined, as shown in Figure 2B. The FPR represents the percentage of time that a method incorrectly classifies a sample as containing AM. Each method has a specific threshold that is used to classify the presence versus absence of AM. As the random forest classifier is based on probabilistic values, a threshold of 0.5 was used as values above this threshold indicate that more than 50% of trees in the classifier voted for "AM". The cut-of values used to discriminate between AM and no AM for methods a1-a3 were 4, 0.2 and 2, respectively, based on the thresholds suggested by the authors of these methods (Bass et al., 2016; Fukushima et al., 2013; Larsson & Öhlund, 2014). The false positive rate of the random forest classifier was low (1.6%) compared to methods a1-a3 (50%, 19% and 62%, respectively). The false positive rate of methods a1 and a3 was not reported in the original descriptions of these methods (Bass et al., 2013), but was reported to be 2.6% for method a2 (Larsson & Öhlund, 2014), and was thus substantially lower than for the data set analysed in this study.

3.2 Long-term quantification of AM

AM occurred more often during the nighttime compared to the daytime (Figure 3A), two-sample t-test, all p-values < 0.001. At locations H1 and H2, which were within 1.3 km of the nearest wind turbine, outdoor AM occurred on



average for more than 50% and 25% of the nighttime and daytime, respectively. Similar trends were also observed at location H3, but with a lower prevalence of around 25% AM during the nighttime and only 3% during the daytime, where the nighttime value is comparable to previous observations for similar distances (Kristy L Hansen et al., 2019). A larger number of AM events were detected outdoors compared to indoors, with the exception of location H3 during the daytime, as shown in Figure 3B. On average, outdoor AM prevalence was approximately 1.5 times higher than indoor prevalence (See Nguyen, Hansen, Catcheside, et al. (2021) for further details). The outdoor-to-indoor AM prevalence reduction at H1 and H2 was similar, ranging between 1.5 and 2.2. In contrast, the difference between outdoor and indoor AM prevalence was smaller for data measured at H3 during the nighttime (reduction = 1.1), and indoor AM occurred more often than outdoor AM during the daytime (reduction = 0.4).



Figure 3. Outdoor and indoor AM prevalence and AM depth. **A**, AM prevalence percentage difference during the nighttime and daytime. **B**, AM depth distributions measured indoors and outdoors at three locations with median values indicated by vertical red dashed lines. **C**, comparison between indoor and outdoor SPL. Outdoor SPL distributions with median values are shown on the top and side, respectively. **D**, indoor and outdoor background noise as calculated for data measured when then wind farm power output capacity < 1%.

The WFN AM depth measured outdoors and indoors at locations H1-H3 is shown in Figure 3B. AM depth is a measure of the peak-to-trough variation in the overall SPL and is an indicator of potential human disturbance. The AM depth was calculated as $\Delta L_{Aeq,5} - \Delta L_{Aeq,95}$, where Δ represents the difference between the fast- and slow-weighted SPLs (Fukushima et al., 2013). This metric is reported in this study because it has been used in laboratory listening experiments to assess the annoyance potential of AM (Renewable UK, 2013; Yokoyama, Sakamoto, & Tachibana, 2013). The median AM depth measured indoors was higher than that measured outdoors at all three locations, as shown in Figure 3B (two sample t-test, all p < 0.001). These results may be explained by the lower level of indoor noise, as shown in Figure 3D, which would provide less masking than the higher level outdoor noise. At H1-H3, the median indoor AM depth was greater than 2 dBA, and hence most of the AM events could cause a fluctuation sensation for residents within the home, according to Yokoyama et al. (2013). Further results, not shown here, indicated that the AM depth for each octave band was higher than the

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values shown in Figure 3B and the highest AM depth was observed in the lowest 63 Hz octave band (Nguyen, Hansen, Catcheside, et al., 2021).

To examine if differences between outdoor and indoor AM prevalence could be attributed to house insulation, the distribution of simultaneously occurring outdoor and indoor SPLs are presented in Figure 3C. A greater A-weighted SPL reduction was observed for H1 and H2, compared to H3. This may explain some of the differences between the relative outdoor and indoor AM prevalence for H3 (Figure 3A). The outdoor-to-indoor SPL reduction at H3 was relatively lower for outdoor SPLs < 40 dBA. However, it is important to note that the outdoor-to-indoor noise reduction calculated using overall SPLs depends not only on building materials, but also the noise type and indoor background noise characteristics. The lowest level of indoor background noise measured inside during periods when the wind farm power output was less than 1% was higher for H3 than for H1 and H2 (see lower confidence interval limit in Figure 3D). This may have affected the relationship between indoor and outdoor SPLs shown in Figure 3C, although the Figure 3D results could also be affected by the availability of data at such low power outputs. Although it is not very accurate to characterise the outdoor-to-indoor reduction using overall SPLs (K. Hansen, Hansen, & Zajamšek, 2015; Thorsson et al., 2018), this is a simple approach and the results are easy to interpret.

3.3 Diurnal and seasonal variability

AM occurred most frequently at nighttime between 10pm and 4am and the lowest AM prevalence was observed between 10am and 2pm (Figure 4A). Similar distributions of AM prevalence were observed at H1 and H2. For these locations, the highest and lowest AM prevalence were approximately 60% and 20%, observed at 12am and 12pm, respectively. For location H3, less than 5% of AM prevalence was observed during the daytime, but this number increased to more than 30% during the nighttime. The background noise was also found to be lower during the nighttime compared to the daytime, as shown in Figure 3D, which was anticipated due to a reduction in human activities during the nighttime. Higher AM prevalence observed during the nighttime could be partly attributed to lower background noise levels at nighttime compared to the daytime.

The mean AM prevalence was not notably different between seasons, as shown in Figure 4B. However, when AM prevalence was averaged over each hour, as shown in Figure 4C, clear monthly and hourly variations of AM were evident. At all measurement locations, during the winter and spring months, AM prevalence significantly increased after sunset which occurred at approximately 5pm and 8pm in the Winter and Summer months, respectively. A relationship between sunrise and reduced AM prevalence can also be observed in Figure 4C. This overall pattern is consistent with the Larsson and Öhlund (2014) findings, where the authors observed a strong association between AM prevalence and solar elevation angle.

3.4 Noise diary and associated acoustic data

A total of 167 annoyance (Participant 1: N = 112, Participant 2: N = 55) noise diary entries were collected over one year by two participants residing at H1 and H2. Fifteen entries were rejected due to missing acoustical, weather station and/or participant rating data, as well as wind speed > 5 m/s, resulting in a final number of 152 annoyance entries (Participant 1: N = 105, Participant 2: N = 47). No noise samples were excluded based on rain as weather data indicated that rain only occurred during 1.4% of all noise recordings over one year. This low prevalence of rain is believed to have negligible effect on the results and furthermore, the AM detection algorithm was developed on data containing rain. All noise diary entries were made inside the house. The noise diary entries often spanned entire nights, making their analysis challenging as participants were likely asleep during most of the annoyance period.





Figure 4. Diurnal and seasonal variation of AM characteristics. **A**, diurnal variation of AM prevalence. Thicker lines are the average trend over the year for three locations. Light lines indicate the trend for each month. **B**, seasonal summary of AM prevalence, calculated as the mean AM prevalence over each season (i.e., Summer from Dec-Feb, Spring from Mar-May, Winter from Jun-Aug and Autumn from Sep-Oct). **C**, relationship between diurnal and seasonal variation of AM prevalence. Dashed lines indicate sunset and sunrise time.

Both study participants reported annoyance throughout the year, with the highest number of events in Winter (May, June and July) and lowest in Summer months (December, January, February), as shown in Figure 5A. All noise events were self-reported from inside the house, predominately in the bedroom. On average, Participants 1 and 2 recorded at least one annoyance period per day on 30%, and 16% of the days of the year, respectively. However, during winter months they reported annoyance for up to 45% and 50% of the days, respectively. The greatest number of noise diary entries were recorded in the late evenings and early mornings, as shown in Figure 5B. Most noise diary entries were recorded when participants were "very" and "extremely" annoyed, corresponding to a rating of 4 and 5, respectively (Figure 5C). Both participants were highly annoyed for at least 40 days in the year and noise diary entries were usually recorded when they were at least moderately annoyed (i.e. rating of 3). Both participants most often described the noise as a type of "swoosh" as seen in Figure 5D. The associated annoyance for this type of noise varied widely between a rating of 2 and 5 for Participant 1 and between a rating of 3 and 4.5 for participant 2. On the other hand, while "rumble" or "swoosh rumbling" noise occurred less frequently, it appeared to be more consistently associated with higher annoyance ratings.





Figure 5. Noise diary data overview, N = 152 after reduction due to missing data. **A**, annoyance entry counts per month. **B**, annoyance entry counts per hour of the day. **C**, annoyance entry counts per annoyance rating. **D**, the relationship between annoyance ratings and noise descriptors.

The power spectrum for the "highly annoyed" cases was markedly higher than the "not highly annoyed" cases at H1 and H2, as evident in Figure 6A, which shows the median spectrum calculated over each noise diary entry duration. For Participant 1, the "highly annoyed" ratings were consistent with higher A-, C- and G-weighted SPLs, as well as higher wind farm power output (Figure 6B and C). However, the difference between "highly annoyed" and "not highly annoyed" for Participant 2 was noticeably smaller than for Participant 1, which could be due to various reasons including participant noise perception, wind farm noise characteristics, annoyance recording timing, building insulation properties or other potential biases. Different trends were observed for wind direction at each residence, where the direction corresponding to "highly annoyed" was downwind for H1 and crosswind for H2 (Figure 6D).



Figure 6. **A**, indoor power spectral density comparison between "Highly annoyed" (HA) and "Not highly annoyed" (Not HA). **B**, wind farm power output. **C**, A-, C- and G-weighted indoor sound pressure level. **D**, relationship between wind direction and annoyance.



4 DISCUSSION

This paper presented a summary of a comprehensive field study focused on wind farm AM. To the best of our knowledge, this is the first study to detect wind farm AM using a validated, machine learning-based algorithm and to characterise and quantify AM using comprehensive data measured near a wind farm. This is also the first study to analyse simultaneous long-term acoustic, meteorological, and annoyance data measured within a few kilometres from a wind farm.

Wind farm AM is a challenging signal to detect, as its characteristics vary depending on meteorological conditions. As a result, the spectral content and time varying features are not constant. Despite these changes, the human auditory system can still recognise the presence of wind farm AM. Thus, for an automated AM detector to achieve performance close to humans, it needs to incorporate a range of specific acoustical features. In this study, the selected features included indicators of noise level variation, tonality and low-frequency content. The resulting algorithm significantly outperformed previous AM detection methods and demonstrated performance close to human scoring. These findings support the idea that human perception of AM is more complex than assumed by previous AM detection methods that are based on noise level variations alone. Hence, it is not surprising that the method presented here achieved substantial improvements in performance compared to previous methods.

Consistent with previous studies, wind farm AM occurred most often during the nighttime (Conrady et al., 2020; Kristy L Hansen et al., 2019). Furthermore, a remarkably strong temporal relationship between sunset and sunrise times and the beginning and end of AM was observed. These trends were expected as nighttime provides favourable weather conditions for sound propagation, which include stable atmospheric conditions, high humidity, strong temperature inversions, and high wind shear (Stull, 1988). During these conditions, sound waves are refracted towards the ground surface in downwind and crosswind directions (although wind shear does not contribute in the latter case) (Ostashev & Wilson, 2016). Consistent with the prevalence of AM, residents reported annoyance most often during the nighttime and early morning. The residents were "highly annoyed" most often during different wind directions, although these results may have been affected by the prevailing wind directions at H1 and H2. The high annoyance reports and prevailing wind direction were consistent at each residence and were found to be downwind and crosswind, respectively (see Supplementary Material in Nguyen, Hansen, Catcheside, et al. (2021)). Thus, AM was more prevalent and annoying during conditions favourable to WFN propagation.

A large difference was found between outdoor and indoor AM. At long-range, spectral imbalance of wind farm noise arises due to the higher atmospheric and ground absorption at mid to high frequencies (Ostashev & Wilson, 2016). In fact, Kristy L Hansen et al. (2019) found that AM usually occurs at very low frequencies (i.e., around 50 Hz) at several kilometres from a wind farm. In addition, low-frequency noise is poorly attenuated by building structures, resulting in lower outdoor-to-indoor noise level reduction at low frequencies (K. Hansen et al., 2015). These results could explain the relatively small outdoor-to-indoor reduction in AM prevalence that was observed at H3 at nighttime. The increase in AM events measured indoors during the daytime at H3 may have been a result of high outdoor ambient noise that masked the outdoor AM but not the indoor AM. These findings suggest that the outdoor-to-indoor noise reduction also impacts AM prevalence. Also, a greater AM depth is associated with higher annoyance (Lee et al., 2011; Schäffer et al., 2016; Yokoyama et al., 2013), and thus AM may be more annoying when people are indoors with low ambient background noise, which is exaggerated during the nighttime. These observations are particularly relevant for cases where AM is only measured outdoors.

There were no significant differences in outdoor AM prevalence between seasons, considering combined daytime and nighttime data. This contrasts with the study conducted by Conrady et al. (2020) where the authors reported more frequent AM during the Winter compared to Spring, but with more limited data from a much colder climate in Sweden. Despite the lack of difference in AM prevalence between seasons, both participants reported annoyance more often during the Winter months. This may have occurred due to more stable environmental conditions at nighttime during winter compared to other seasons, a phenomenon that was observed at a nearby location (within 100 km) to this study (Zajamšek et al., 2016). Van den Berg (2008) showed that while stable atmospheric conditions occurred less often in the spring and summer compared to the autumn and winter, a relatively high percentage of the shorter summer nights exhibited a stable atmosphere. Therefore, relatively more annoyance recordings in winter could reflect other factors apart from AM prevalence, including a greater sundown period, during which people are more likely to be indoors and trying to relax or sleep. These factors need to be considered in addition to AM prevalence when predicting seasonal variations in annoyance.

Substantial differences in the noise level and frequency content were observed when residents reported that they were "highly annoyed" as opposed to "not highly annoyed." When residents reported high annoyance, the largest spectral differences occurred at infrasonic frequencies (< 20 Hz) and at mid-frequencies (200 - 600 Hz). The



measured infrasound contained the blade-pass frequency and harmonics extending up to approximately 10 Hz, typical of wind farm noise (Zajamšek et al., 2016). The mid-frequency noise components were consistent with "swish" noise, which is dominant at 500 Hz (Doolan, Moreau, & Brooks, 2012). Although differences in SPL up to 20 dB were observed at infrasonic frequencies, the associated SPLs were well below the normal hearing threshold (ISO389-7, 2005). Additionally, neither participant recorded any symptoms that have been claimed to be associated with infrasound exposure such as nausea, pressure (or fullness) in the ears and/or dizziness (Maijala et al., 2021; van Kamp & van den Berg, 2018). Thus, annoyance was most likely associated with the increased SPL at mid-frequencies, as this is consistent with the "swish" character mentioned in the noise descriptors chosen by both participants. In fact, all noise descriptors chosen by the participants indicated that there was AM present in the noise when it invoked annoyance. Hence, there was good agreement between noise diary entries and acoustic data in terms of both SPL and frequency content.

Several weaknesses of this study warrant consideration. For instance, the benchmark dataset used to develop the AM detection algorithm may limit its applicability to other datasets due to differences in source-receiver distance, topography, wind farm layout, wind turbine model, prevailing atmospheric conditions, etc. Although we measured comprehensive acoustical data, a limitation of our study is a lack of comprehensive meteorological data measured at hub-height most relevant to the noise source. This limitation calls for better data sharing practices between wind farm operators and researchers (Kusiak, 2016) to allow for more in depth analysis of relationships between wind farm noise and meteorological conditions. Another limitation was that noise diary entries were clearly biased towards annoyance given the nature of annoyance reporting and the fact that few entries for "Not at all" annoying were recorded. Few reports of low annoyance limits the reliability of estimates of the prevalence of annovance and key acoustic features that may help distinguish periods of high versus low WFN annovance. In future work, this could perhaps be avoided by instructing participants to record noise diary entries at random, or at repeated time points during both high versus low AM, as proposed by Janhunen et al. (2017), to allow for a larger range of annoyance ratings to be collected. Alternatively, random sampling methods could be more useful to periodically prompt for annoyance responses without over-burdening participants. This method would also reduce potential biases such as weather, season, apathy, participant burden, socioeconomic status associated with annoyance reporting, which can include missing entries and/or skewing of entries towards when participants are less busy. Another limitation is the small number of participants, which clearly limits generalisability of these results. The generalisability is further limited by several factors influencing annoyance including personal (e.g. apathy), socioeconomic (e.g. wind turbine host or farmer with seasonal work), or methodological (e.g. annovance recording forms on a nightstand by the bed, unknown exact duration of the annoyance periods). Future studies using larger sample sizes, including participants at varying distances from wind turbines and with different attitudes and self-reported annoyance to WFN, are clearly needed to further evaluate AM compared to other acoustic features of WFN that may contribute to WFN annoyance and impacts on nearby communities.

5 CONCLUSIONS

The advanced, automated AM detector developed in this study was based on the random forest approach. This AM detector demonstrated high performance, and substantially outperformed traditional AM detection methods to achieve a classification performance close to that of humans. This AM detector was used to characterise and quantify wind farm AM for a large data set measured over one year at three relatively long-range distances from three wind farms in South Australia. Outdoor AM was present for more than 50% of the nighttime at residences located less than 2 km from the nearest wind turbine. The nighttime AM prevalence was lower indoors than outdoors, but there was an increase in AM depth in the indoor data. The results showed clear diurnal and monthly variations in AM prevalence, indicating a strong relationship between sunset time and increased AM prevalence. This study also explored self-reported annoyance at two locations near two wind farms over one year and showed that the highest annoyance was recorded during the cold winter months in the evening, nighttime and early hours of the morning at times likely to influence sleep. The participants most often described the noise as a type of "swoosh", "swoosh rumbling" and "rumble" at times when acoustic features supported the presence of amplitude modulation. However, small sample size and the potential for a range of possible biases requires careful interpretation of associations between wind farm noise and annoyance.

We hope that, in the future, further insight into the prevalence of AM and associated meteorological conditions, and impacts on humans will help to explain underlying noise generation mechanisms relevant to human perception. Ultimately, this will improve the design of wind turbines such that they are less disturbing and hence, more acceptable to surrounding communities.



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