Noise and Pressure Profiles in the Vicinity of Wind Turbines

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Abstract

With the increasing popularity of renewable sources of energy, there is also increasing awareness of their potential hazards. Wind energy has faced some of the most scrutiny in recent years because of the production of low frequency noise by wind turbines. Chronic exposure to sound of low frequencies has been shown to cause adverse health effects, which has raised concerns about wind farms in close proximity to people's homes. Our measurements of the sound in the vicinity of wind turbines found frequencies in the range of concern, but they were indistinguishable from the sounds of the wind. This experiment was unable to detect the low frequency noise from a wind turbine, meaning it is likely not a concern for the people living nearby.

Introduction

I. Production of Low Frequency Noise

A large point of concern regarding wind turbines is their production of Low Frequency noise and infrasound. Low frequency noise (LFN) is sound with a frequency in the range of 20Hz to 200Hz. Infrasound has a frequency in the range of 1Hz to 20Hz (Bolin 2011).

Wind turbines produce noise from the mechanical components in the nacelle, (the center box containing machinery) and from the movement of the blades through the surrounding air. Mechanical Noise is generally not a concern in modern wind turbines because of advanced sound insulation technology. Most sound produced by wind turbines comes from three different kinds of aerodynamic interactions between the blades and the wind. The first kind occurs when a blade passes near the tower at the lowermost part of its rotation. This sound usually has a frequency between 1 and 30 Hz and is dependent on the speed of the blade rotation. It is often too quiet to be detected by the human ear. The second source of sound is the trailing edge noise due to the airfoil shape of the blades. This sound occurs in a higher frequency range of 500Hz to 1000Hz. The last source comes from turbulent flow of the air around the blades. The turbulent flow amplifies the naturally low frequency noise produced by wind. This sound can have frequencies between 10 Hz and 200 Hz, and is the main concern surrounding LFN from wind turbines (Bolin 2011).

Sound of these frequencies is capable of traveling significantly further than sound of higher frequencies, meaning it can potentially have an effect on the people who live near wind farms.

II. Health Effects of Low Frequency Noise

There have been many claims that low frequency noise leads to adverse health effects. Countless studies have shown LFN to cause sleep disturbances, insomnia, headaches, nausea, and in more extreme cases panic attacks and tinnitus. Even in the absence of severe symptoms, LFN has been shown to cause annoyance to listeners. One study done on people working in an office building reported that two thirds of the participants felt relief when the air conditioner (a common source of LFN) was turned off. An explanation for this is that the brain puts a large amount of effort into keeping LFN from being recognized by higher centers of awareness. Over long periods of time, this annoyance can lead to a decrease in productivity, higher levels of stress, and fatigue (Persson Waye, 2011).

These symptoms have also been reported by people living near wind farms, and is often referred to as "wind turbine syndrome". The majority of studies concerning LFN have looked at the effects of noise from ventilation units and automobiles, and the results from studies about wind turbine noise are inconsistent. Although there are conflicting opinions among experts about how much harm is actually caused by LFN from wind turbines, they produce sound within the low frequency ranges that have been shown to be harmful making them a safety concern for the people living near them (Persson Waye, 2011).

III. Opposition to Wind Turbines

Wind power has faced both political and social opposition because of their production of LFN. Throughout the world, wind power has been shot down by politicians and power companies have been sued for disturbances caused by the turbines. The construction of several wind farms in Central Illinois in the past few years (and more to come in the next few years) has sparked controversy amongst the residents of nearby towns. The distance that a wind turbine must be from houses and other buildings is the most controversial subject of discussion. The proposed required distance for a new wind farm in Paxton, IL is 1,500 feet, which is 500 feet further than the distance required by the Ford County Wind Ordinance (2008). But residents have still been lobbying for a greater requirement of 2,250 feet, with some even pushing for 3,250 feet. The setback distances are so widely debated because there is not a consensus on how far the low frequency noise from a wind turbine can travel. This experiment will attempt to detect low frequency noise in the vicinity of a wind turbine, and track the frequencies at different setback distances (Brumleve 2018).

IV. Purpose of This Study

The purpose of this experiment is to record the sound of a wind turbine to see if low frequencies are detectable at different distances up to 1600 feet. When standing near the wind turbine, a constant low humming noise was audible. The sound was recorded by a microphone at different distances and fourier transformed so that the frequencies present in the recordings could be seen. The goal of using fourier transformed sound data is to look for a constant, low frequency sound that dissipates as distance from the turbine increases. This sound should be present regardless of the amount of wind or point in time. In this paper, trends within the sound data are investigated for varying distances, frequencies, and points in time. A conclusion about the feasibility of detecting the sound from a wind turbine and recommendations for future research will be made.

Methods

The goal of this experiment is to record the sound of a wind turbine to see if low frequencies are detectable at different distances up to 1600 feet. Trends within the sound data are investigated for varying distances, frequencies, and points in time. A conclusion about the feasibility of detecting the sound from a wind turbine and recommendations for future research will be made.

I. Measurement Device

The measurement device was first put together on four individual breadboards and later recreated as a printed circuit board. The components are shown in *figures 1 and 2* below.

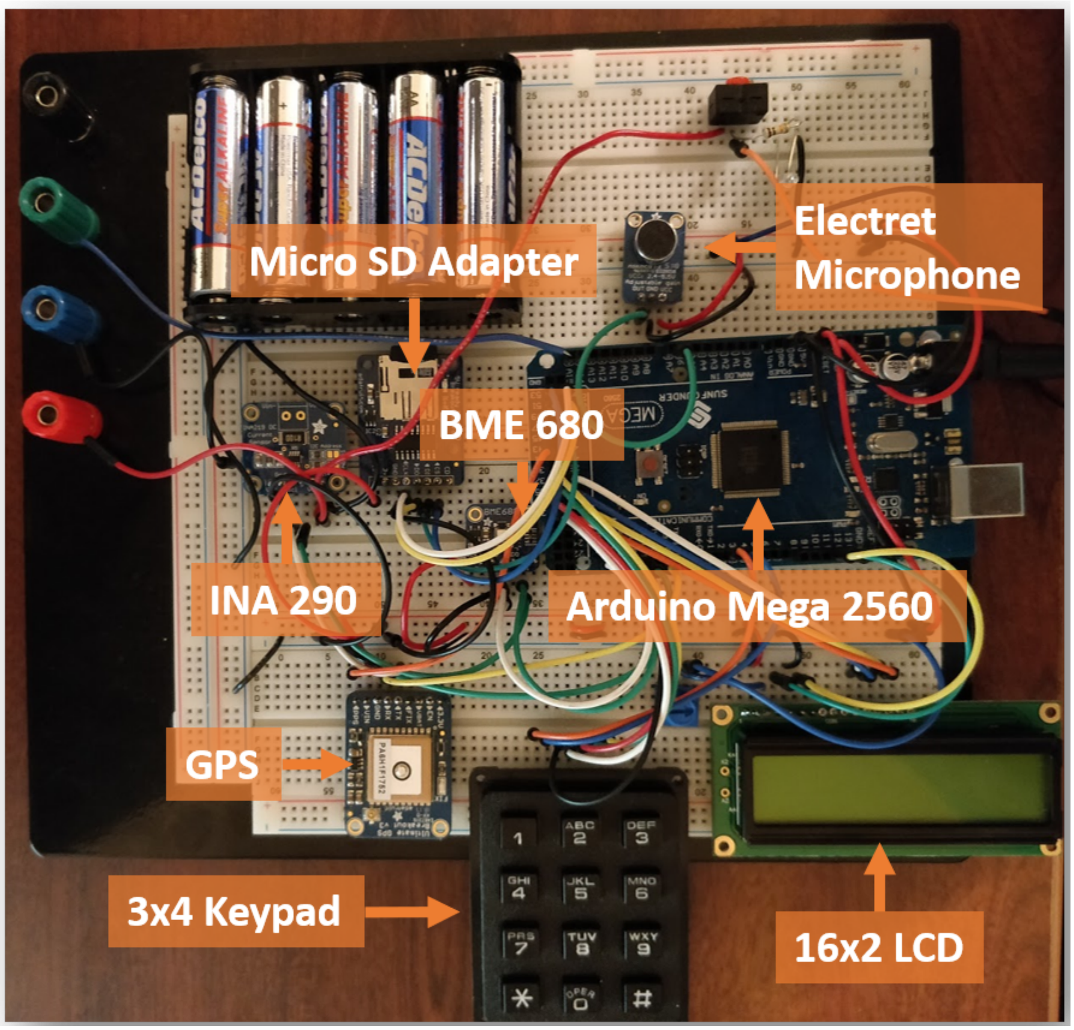


Figure 1: Breadboard Measurement Device.

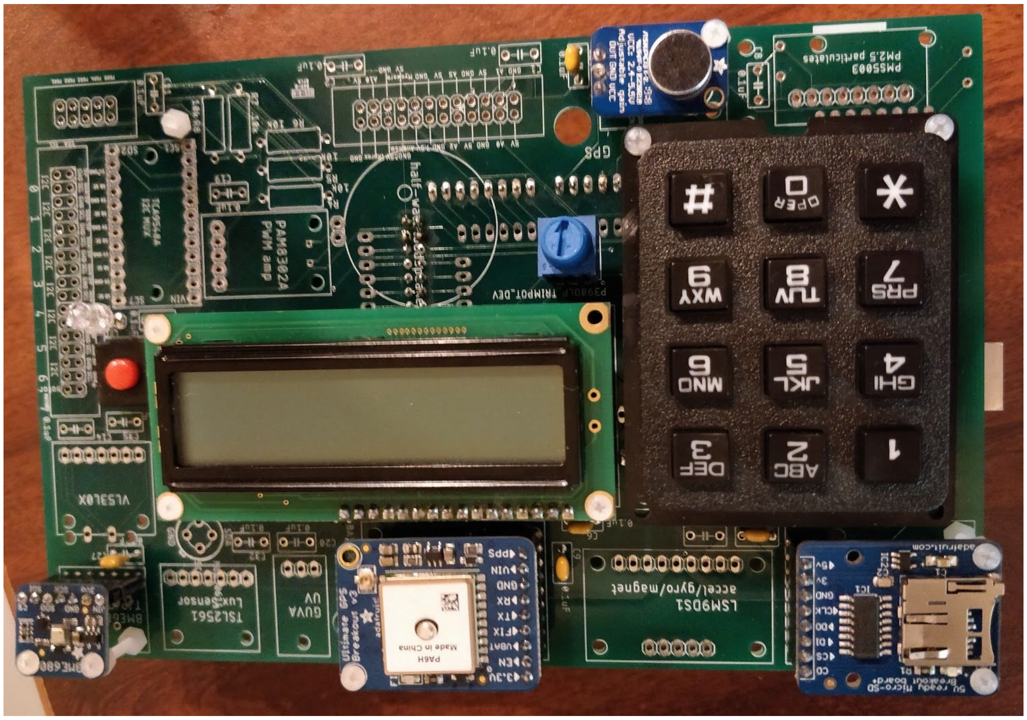


Figure 2: Printed Circuit Board measurement device. The PCB is electrically equivalent to the original breadboard.

Measurement components:

1. Arduino Mega 2560
2. Electret Microphone - Record sound
3. BME 680 - Measure temperature and pressure
4. GPS - Track location of each measurement
5. Anemometer - Measure wind speed

Microphone

The microphone we are using is a MAX4466 microphone. The frequency range for our microphone is for 20 Hz to 20 KHz. It also has a gain setting which can be set between 25x to 125x range, which down to be about 200 mVPP (where VPP stands for Voltage Peak to Peak). For loud noises the max it can go is 5 VPP. The input voltage range for our microphone is 2.4 V to 5 V DC max. The quietest electrical noise we can get from a microphone is by giving 3.3 V as input voltage. The microphone uses an “Analog-to-Digital Converter” (ADC). The microphone passes an analog voltage to the ADC between 0 V and the microphone’s input voltage, in our case 3.3 V. The ADC converts the analog signal (voltage height) to a digital signal (on/off switches in binary format representing the voltage). In our arduino, the ADC converts the 0V-3.3V to a number between 0-1023, as its ADC has 10 bits.

II. Wind Turbine Specifications

The wind turbine we performed measurements on belongs to the Twin Groves Wind Farm, in Armstrong, IL, about 30 minutes East of Champaign. It is a Vestas V82 1.65 MegaWatt turbine (Farm Facts). The tower is 108 meters tall and the rotor diameter is 82 meters (Bauer 2020).

Figure 3: Wind Turbine at location 40.203677, -87.875488.

III. Data Acquisition Software

The main goal of the data acquisition (DAQ) software was to record the sound, temperature, pressure, GPS location, and wind speed at different locations in the vicinity of a wind turbine. The DAQ would also organize that data recorded by each device.

The Arduino IDE software was used to write, compile, and upload the code to the Arduino Mega 2560. The data acquisition code was written in C++. Initially, we were provided with different codes that separately recorded the data. We then integrated the codes into two separate programs. The first program is the *GatheringProgram.ino*, which records temperature, pressure, GPS location, and wind speed. The second one, *SoundRecord.ino*, records sound, and was provided in the course materials. The sound recording code records at 32 KHz and writes to a binary file code. *GatheringProgram.ino* consists of five different elements, where each element deals with different hardware. The first element is *BME680.cpp*. This part of the code reads temperature and pressure data from the BME680. The code collects temperature and pressure data and puts the data in a single header file which can be displayed on an LCD. The second element of *GatheringProgram.ino* is *GPS.cpp*. This code collects location and time data from the GPS sensor. The third element is *LCD.cpp*. This code displays different sets of data on an LCD when the data is being recorded. The fourth element is *SD2.cpp*. This code uploads all the data onto a micro-SD card. The fifth element is *ANE.cpp*. This code collects wind speed information and calculates the wind speed from the analogue signal coming from the anemometer. *ANE.cpp* functions by setting an upper and lower bound on voltage and wind speed. The bounds of voltage is 0.4V to 2.0V and the bounds on wind speed is 0 m/s to 32 m/s. This code reads analogue values and converts them to sensorVoltage. If the sensorVoltage is lower than the minimum voltage, then the wind speed is set to 0 m/s and if the sensorVoltage is in the proper range the code calculates the wind speed using formula[1]. *GatheringProgram.ino* merges all of the previous code into one program which manages our UI. Our data acquisition software requires two different devices to record data; the *GatheringProgram.ino* is uploaded onto a breadboard Arduino and the sound recording program on a PCB Arduino.

We use two different gathering programs simultaneously because the microphone's 32 kHz analog data requires the use of a buffer. The code is not able to write fast enough onto an SD-card as it records data, so it needs to be saved on to the Arduino in packets of data in the buffer. These buffer packets are then written onto the SD-card. *GatheringProgram.ino* doesn't need a buffer to write onto the SD-card. To match the data saved by both programs, we adapted the naming method in the *SoundRecord.ino* into the *GatheringProgram.ino*. We end up with two micro-SD cards with files of similar names and different data.

IV. Data Acquisition Procedure

Data was gathered in the afternoon of April 18, 2020, at a wind turbine in Armstrong, IL. Four PCBs and two breadboards were used. They were grouped into three separate pairs; group A, group B, and group C. In each set one device was used for recording sound, and one was used for recording temperature, pressure, wind speed, and GPS location. The devices were placed on tables to minimize movement during recording. A tape measure was used to measure the distance of each data point from the wind turbine. Group A recorded at distances of 0, 50, 200, 350, 500, 650, 800, 950, 1100, 1250, and 1600 feet from the turbine tower. Group B recorded at distances of 0, 100, 250, 400, 550, 700, 850, 1000, 1150, 1300, and 1600 feet from the turbine tower. Group C recorded at distances of 0, 150, 300, 450, 600, 750, 900, 1050, 1200, 1350, and 1600 feet from the turbine tower. All three pairs recorded simultaneously at 0 feet and at 1600 feet, to allow for comparisons between the data from each pair of devices. The other data points were taken semi-simultaneously. Group A was placed at 50 feet, one minute later group B was placed at 100 feet, and one minute after that group C was placed at 150 feet. Group A recorded for four minutes, and was then moved to 200 feet, Group B was moved to 250 feet after four minutes, and group C to 300 feet. This process was repeated up to 1350 feet. The 1600 ft data point was approximately equidistant with the wind turbine we used and the other wind turbines nearby. This will be used as a control for potential sound from surrounding wind turbines.

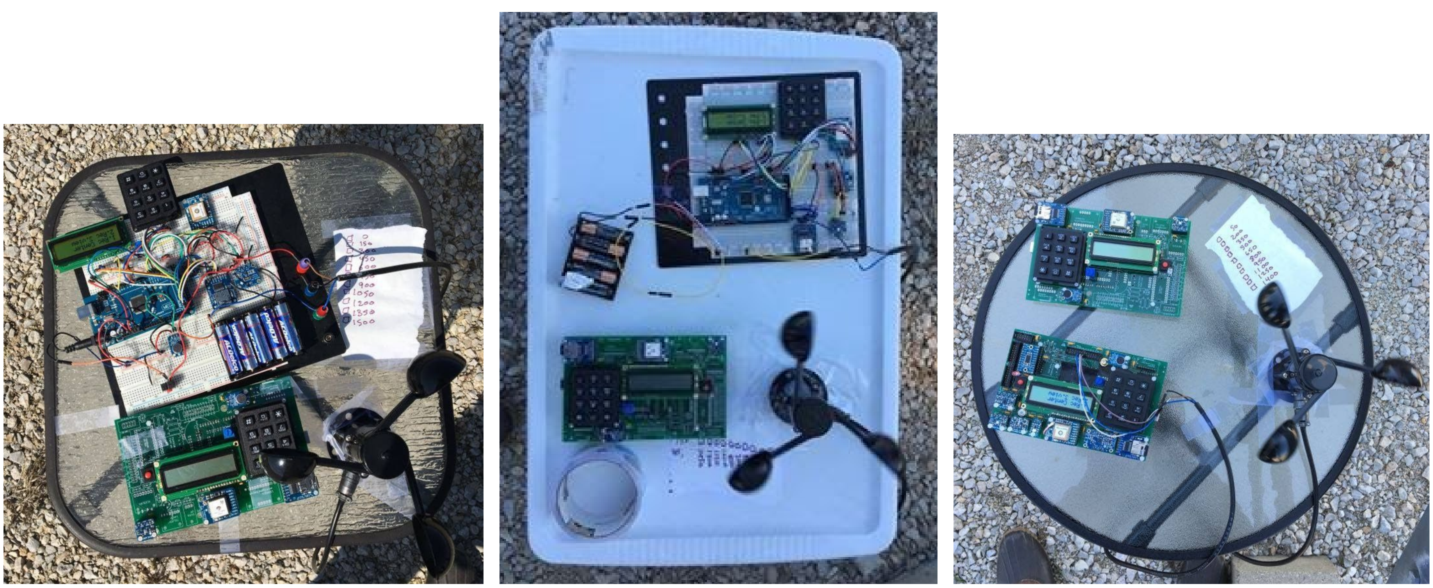


Figure 4: Data Acquisition Setup.

From left to right: group A, group B, group C

Figure 5: Simultaneous recording of data.

V. Data Analysis Procedure

The raw sound data from the measurements is composed of pressure data as a function of time. For the purposes of the study, the frequencies of sound in each of the recordings needed to be found. This can be done using a Fourier Transform. A Fourier Transform is an integral transform. It decomposes a function into its frequencies. One inspiration for the Fourier transform comes from the study of the Fourier series, in which a complicated periodic function (a function which repeats itself after some time period) is written as sum of sines and cosines. A Fourier Transform is an extension of the Fourier series that results when the period of the represented functions approaches infinity. The Fourier Transform of a function of time is a complex valued function of frequency, whose magnitude represents the amount of the frequency present in the original function, and whose argument is the phase offset of the sinusoid in that frequency. The Fourier Transform is not limited to the function of time, but the domain of the original function is commonly referred to as the time domain. For the purposes of this experiment, the function in the time domain is the pressure as a function of time obtained from the data recorded.

$$\hat{f}(\xi) = \int_{-\infty}^{\infty} f(x)\, e^{-2\pi i x \xi}\, dx,$$

The Data analysis code for Fourier transform is written in Python. The code is written in a jupyter notebook. The code initiates by importing all the necessary files like audio file reader, “numpy”, which includes all necessary mathematical operations, and “matplotlib.pyplot” which plots all the necessary graphs in python. The second part of the code sets the max buffer value to a fixed value. Then it sets the file name and reads the “.bin” audio file from the library of recordings. It converts the audio file into a data set which can later be used to calculate the frequency. The third part of the code defines the sampling rate. Using this sampling rate it defines the recording time by dividing the file size by the sampling rate. Using this information the code plots all the data points extracted from the audio with respect to time. This shows the intensity of sound recorded at every point in time. The last part of code is where the Fast Fourier Transform (FFT) is applied to the recorded file to extract the frequency information. The built in Fourier Transform function is used, which accepts the different data points and gives back the frequency domain function of those data points. Once the code gets this frequency domain function it plots the frequency vs intensity graph. We have stored six different testing audio files. These files are the recording of a speaker playing to six different frequencies; 80Hz, 90Hz, 100Hz, 200Hz, 300Hz, 400Hz. We run the code on this data to confirm that the code works properly.

VI. Analog To Digital Counts and Decibels

The Analog to Digital Converter (ADC) counts that the arduino is recording corresponds to the amount of noise at an instance in time. When a sound is made, it travels as changes in pressure. The microphone responds to the changes in pressure and lets through a voltage depending on how much pressure it is detecting. The arduino receives the voltage coming from the microphone through its ADC and converts the voltage to a binary number, the size of which depends on the converter. For our experiment, the count goes from 0 (corresponding to 0 Volts) to 1023 (corresponding to 3.3 Volts).

When talking about sound, it is common to refer to the loudness of a sound in decibels (dB). dB is a relative unit of measurement. dB expresses the ratio of one power to another on a logarithmic scale. In our case, the power is proportional to the pressure squared as seen in the following equation:

$$P = \frac{Ap^2}{\rho c} \cos\theta,$$

Where P is power, p is the pressure, A is the area of the cross section, ρ is the density, c is the speed of sound, and θ is the angle between the direction of propagation of the sound and the normal of the surface. (Wikipedia) DB is used for sound because it takes the large scales of the change in pressure squared and shrinks it to units that are easier to talk about. For example 100 dB corresponds to a 100,000 multiplicative change in pressure or 10,000,000,000 multiplicative change in sound power. The following is the equation for converting power to the power ratio represented in dB.

$$N_{\mathrm{dB}} = 10 \log_{10}\left(\frac{P_2}{P_1}\right)$$

Where N is the ratio of power in dB, P_2 is the measured power, and P_1 is the reference power. For our paper, we keep the units in counts so that the data is seen in as raw of form as possible. There are two direct upshots of this choice. First, it lets us catch bad data points that are a result of electronics. Second, seeing changes in pressure more directly and on a larger scale helps exaggerate the structure of the sound.

VII. Data Analysis Graphs

The first step for the data analysis was to graph the raw data that was recorded by the microphone. The data was represented as ADC counts over a period of time. Each ADC count corresponds to the pressure difference at the microphone, which is a result of sound waves. The counts vs. time graph as shown in figure 6 shows the sound wave as a function of time of the recording at 500 feet. Throughout this explanation the 500 feet data point is used as the example.

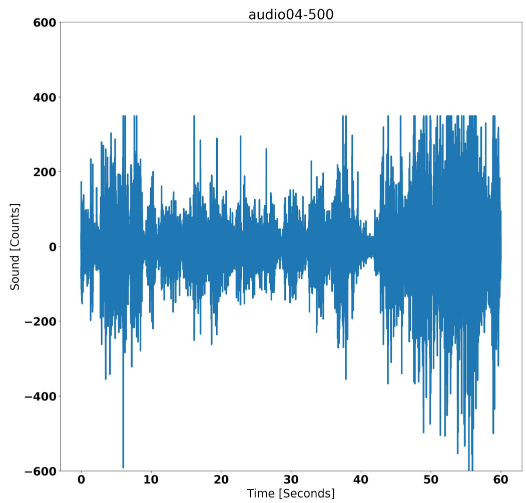


Figure 6: Sound recording at 500 feet

As the recording is taken outside in the wind, it is hard to see any consistent structure in the counts vs. time graph. A structure would reveal if there is noise from a wind turbine. A fourier transform was run on the data to convert it to a function of frequency vs sound count. This graph shows how much sound was recorded for each frequency. A peak at a specific frequency could indicate a noise made by the wind turbine. The result of the Fourier transform for the 500 feet data is shown in figure 7. As a comparison, figure 8 shows the Fourier transform of a middle C (~260 Hz) played on a piano, and a couple of notes above middle C. This data has more distinct frequencies and is easier to interpret.

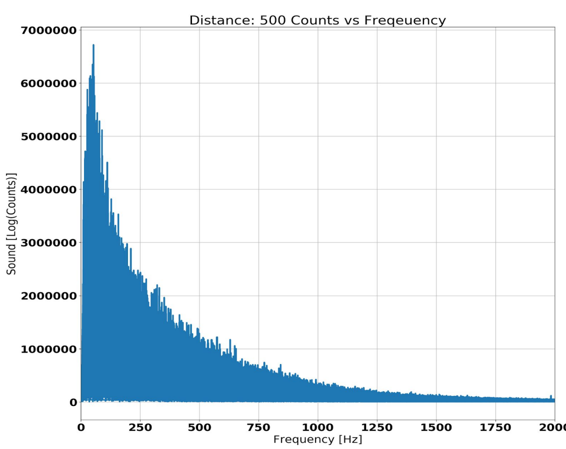


Figure 7: Frequency Graph for 500 feet

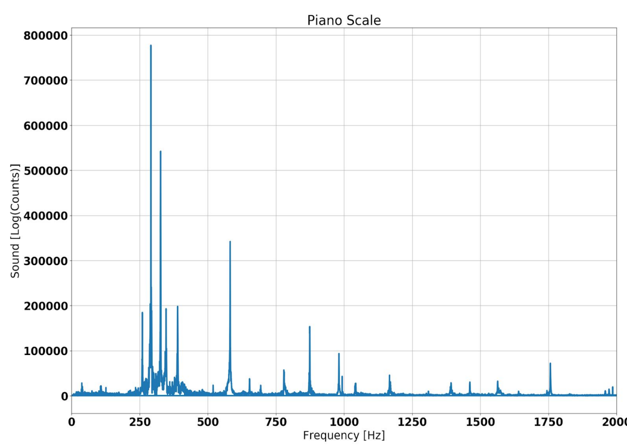


Figure 8: Frequency Graph for piano

The amount of wind in the recording at 500 feet makes the data hard to read and connect a certain frequency to the wind turbine. To reduce the noise in the data, the bin size was decreased by averaging the sound count within small frequency ranges together. Figure 9 shows the data averaged to every 0.1 Hz and figure 10 shows the data averaged to every 1.0 Hz. A log scale was also used to make peaks in the graphs easier to find.

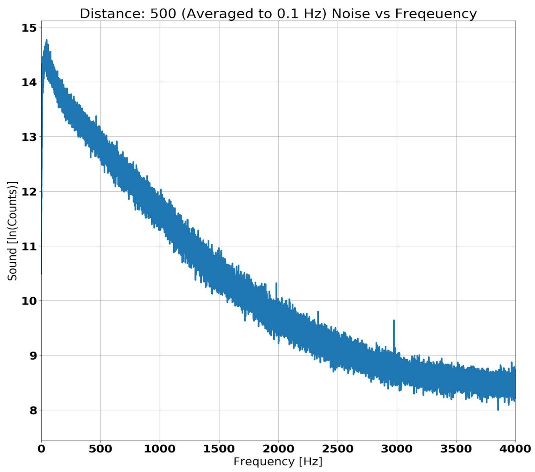


Figure 9: Averaged Frequency Graph for 500 feet, 0.1Hz

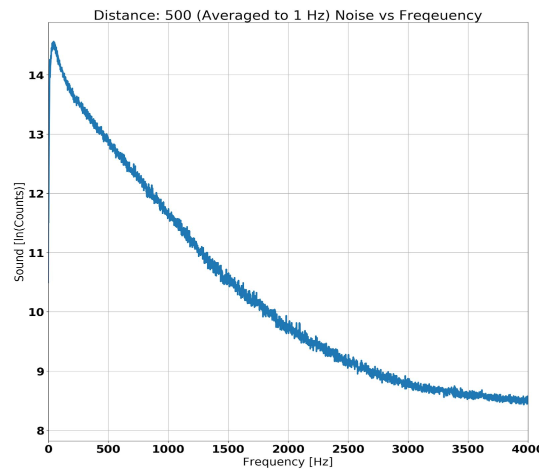


Figure 10: Averaged Frequency Graph for 500 feet, 1Hz

Some details, such as the spike at 3000 Hz in figure 9, are not visible in figure 10. In order to keep as much information as possible, while still removing noise from the wind, the data used in the analysis was averaged to 0.1 Hz.

In order for a frequency spike to be confirmed as wind turbine sound, the same spike must show up at several of the distances. A good way to see a spike in several distances is by overlaying the graphs for different distances to see if any of the peaks align. Distances 450 feet, 500 feet, and 550 feet are shown in figure 11. If any spikes at specific frequencies occured at one of the three data points, they could be compared to other distances on the overlaid graph.

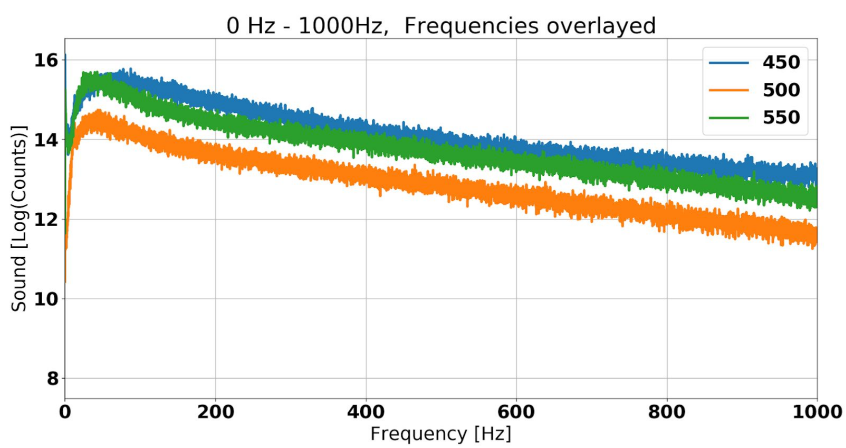


Figure 11: Frequency graph of distances 450, 500, and 550

The frequency graphs would not show a particular peak if the sound created by the wind turbine was audible at some times but not others. In this case, the sum of the counts for a specific frequency might not be higher than other noise. In order to see sounds that occur at regular time intervals, the frequency and sound count must be plotted over time. A spectrogram is a color map that plots frequency over time and indicates the sound count using color. The color scale on the right side of the graph shows that lighter colors correspond to higher sound counts and darker colors correspond to lower sound counts. For example, figure 12 shows the spectrogram of a piano playing middle C (260 Hz), then playing half steps up to a high C. A lighter yellow spot appears for each note played, at the time and frequency at which they were played. If the wind turbine created sounds that occured at regular time intervals, the spectrogram would show light spots at specific frequencies that were consistent over time. The spectrogram for the 500 feet data point is shown in figure 13.

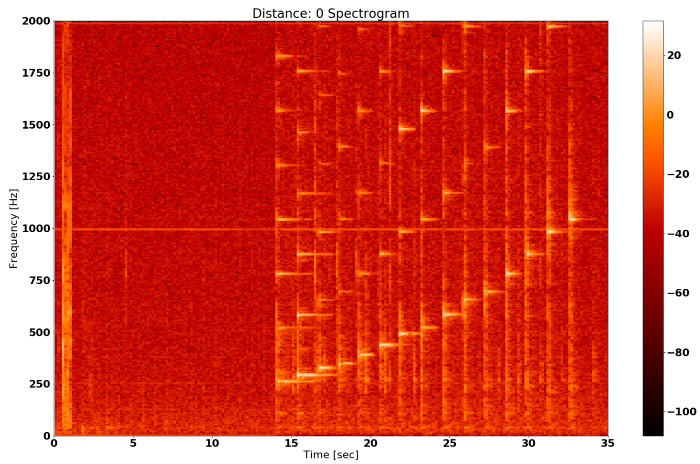


Figure 12: spectrogram of a piano recording

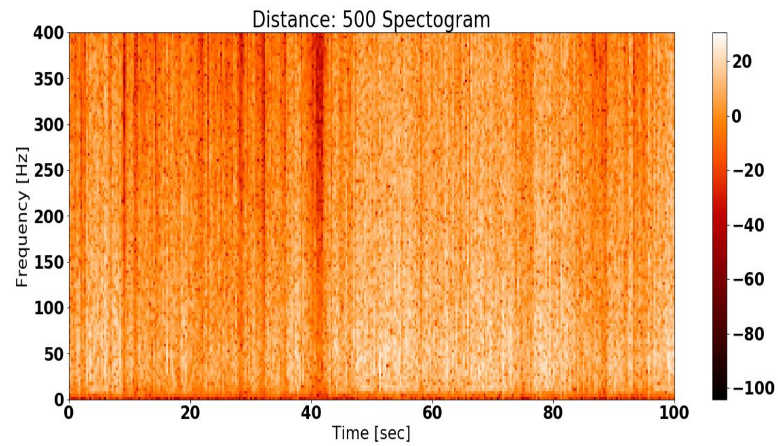


Figure 13: spectrogram of the 500 feet recording

Once certain frequency ranges that look like they could have been produced by a wind turbine are found, they can be plotted as a function of distance to see if there is a trend as the distance from the wind turbine increases. If the sound comes from the wind turbine, it would decrease as the recordings get further away. Figure 14 is an example of data from device A at 5 different frequency ranges. The data shows how much sound from the specific frequency range was present at each distance.

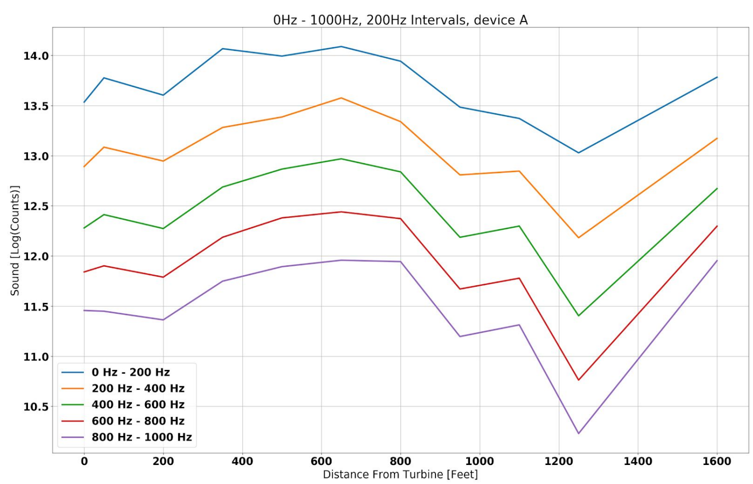
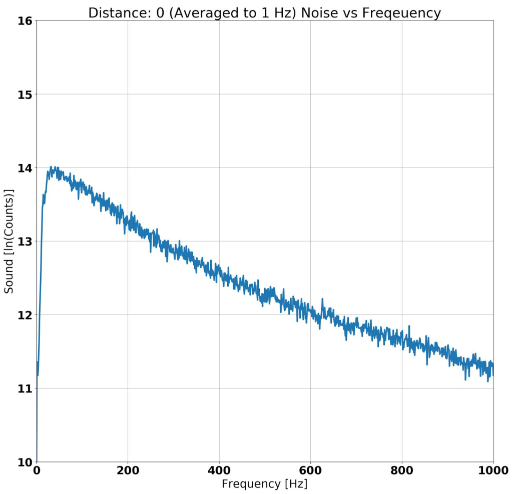


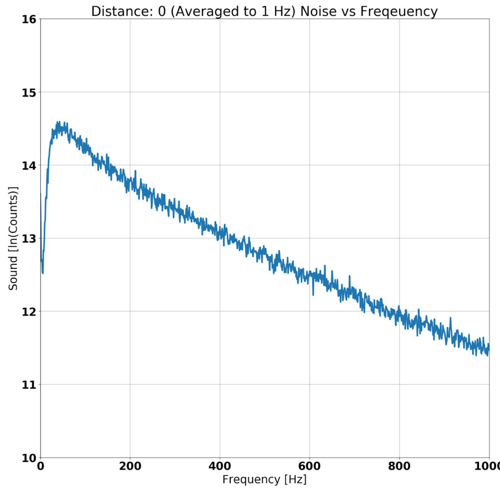
Figure 14: Distance graph for device A, from 0 Hz to 1000 Hz

Results

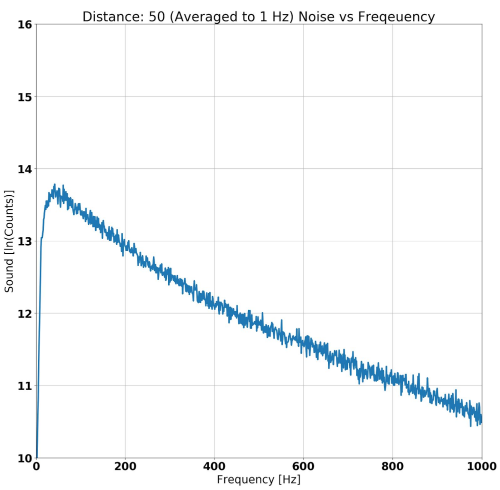
ADC count for each data point, averaged to 1 Hz:



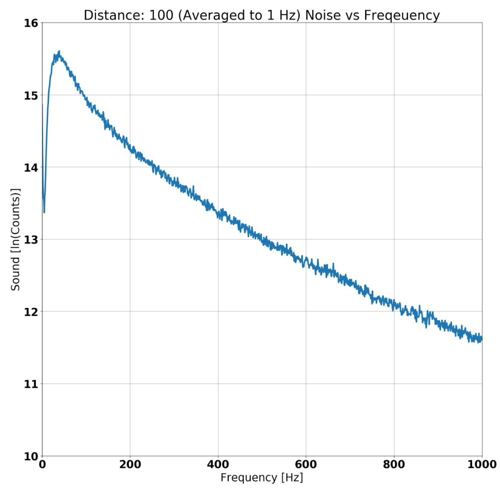
0 ft: Device A



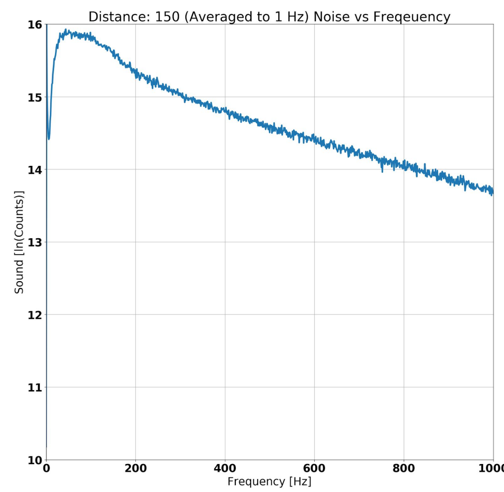
0 ft: Device B



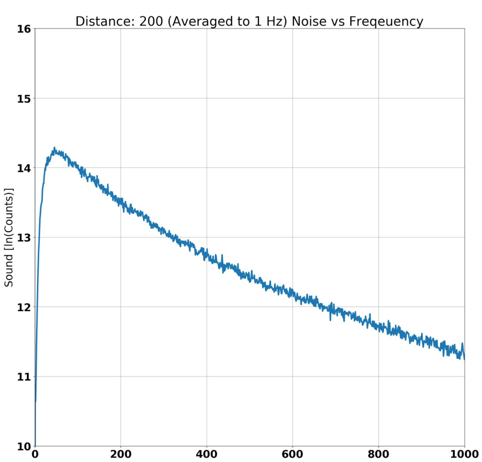
50 ft: Device A

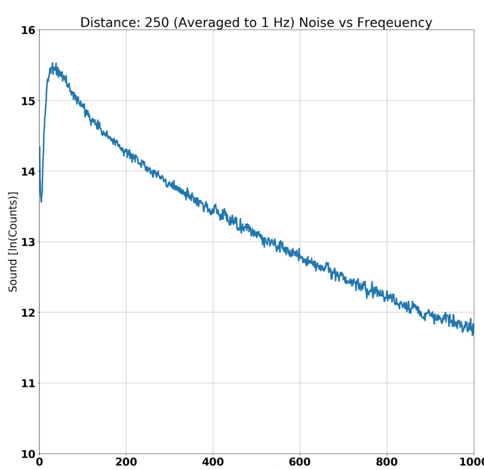


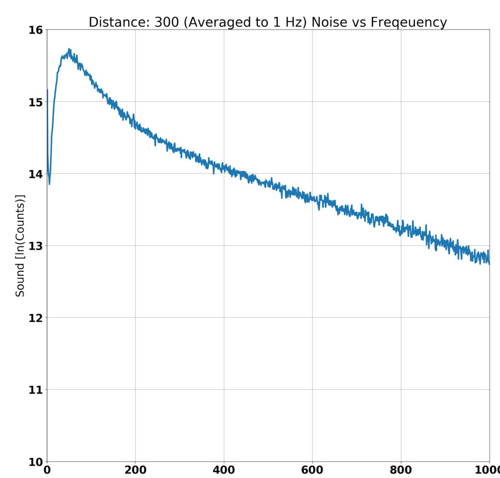
100 ft: Device B



150 ft: Device C



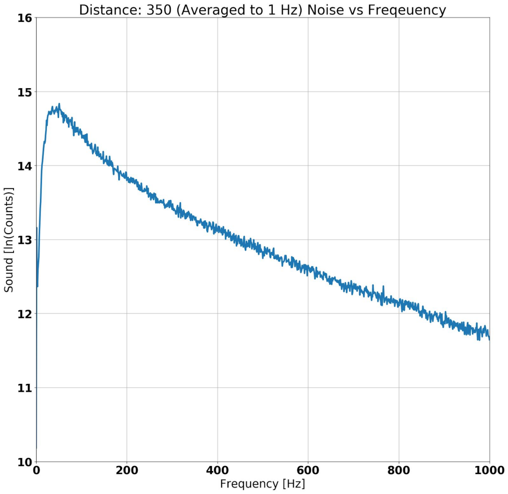




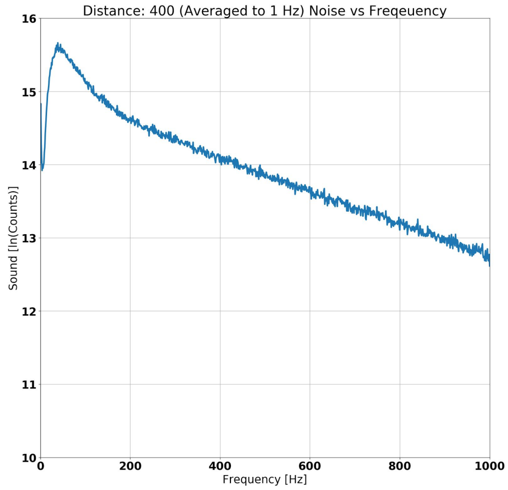
200 ft: Device A

250 ft: Device B

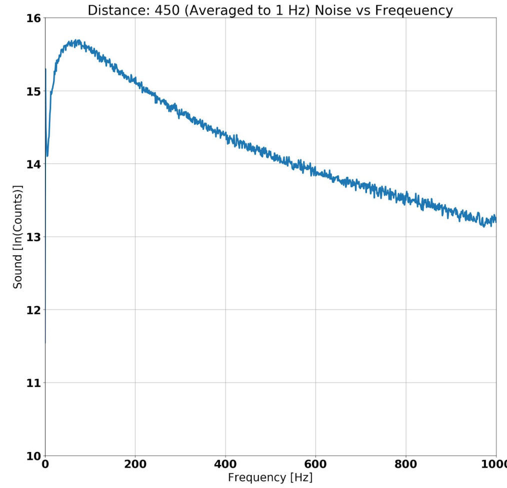
300 ft: Device C



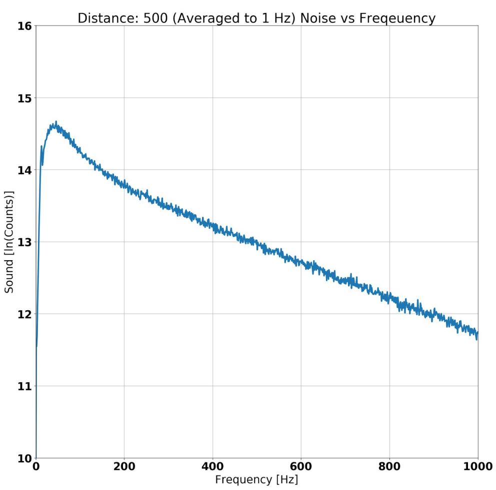
350 ft: Device A



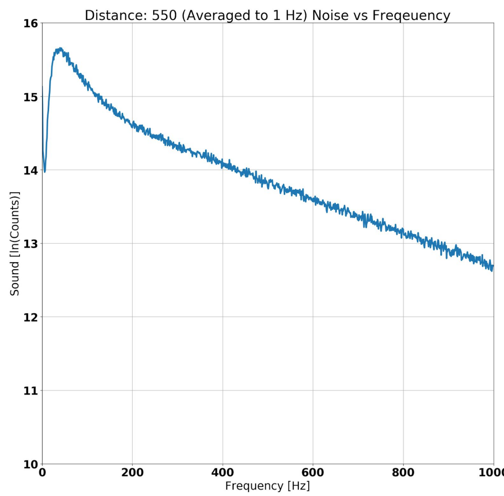
400 ft: Device B



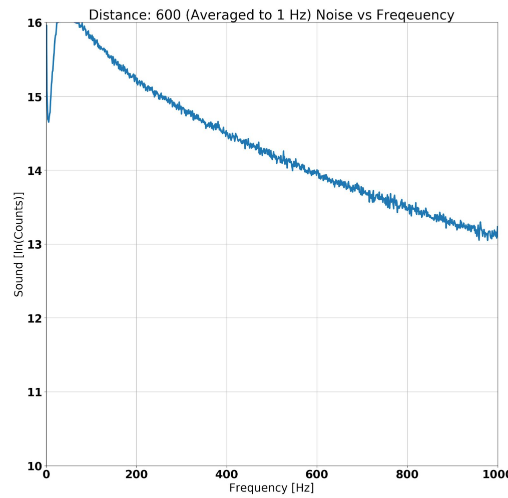
450 ft: Device C



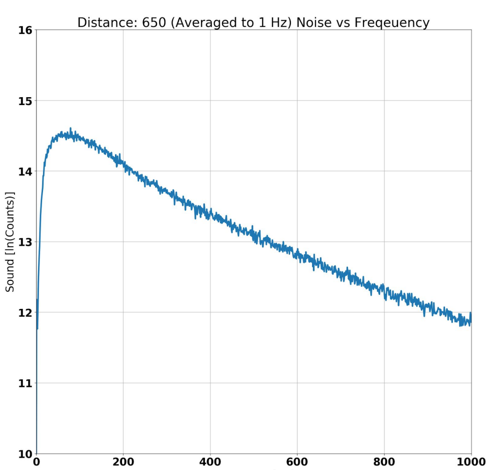
500 ft: Device A



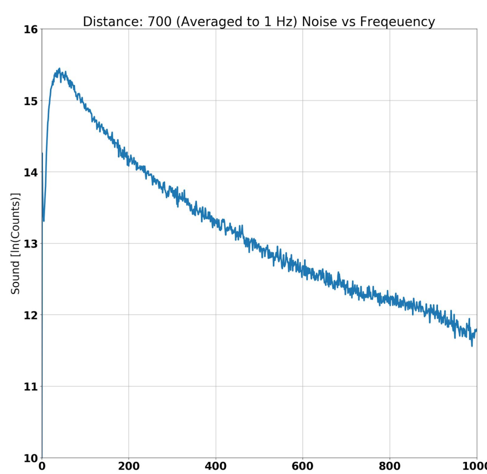
550 ft: Device B



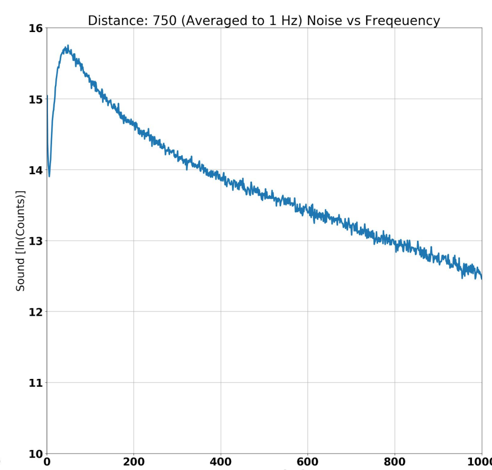
600 ft: Device C



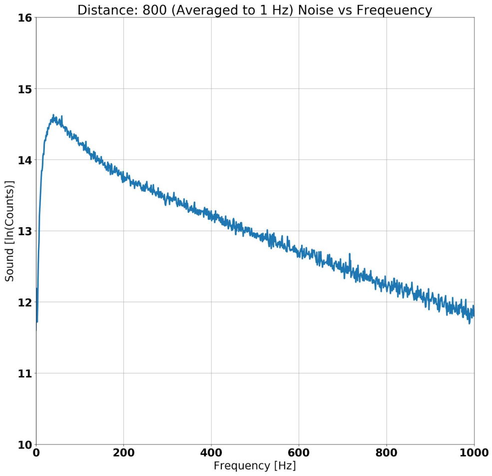
650 ft: Device A



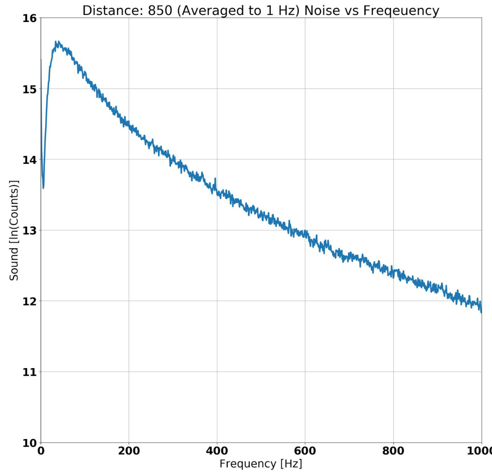
700 ft: Device B



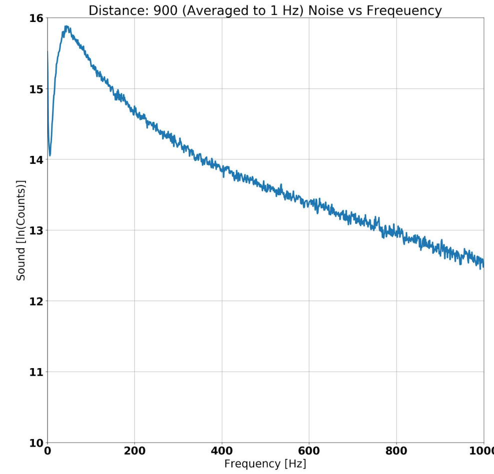
750 ft: Device C



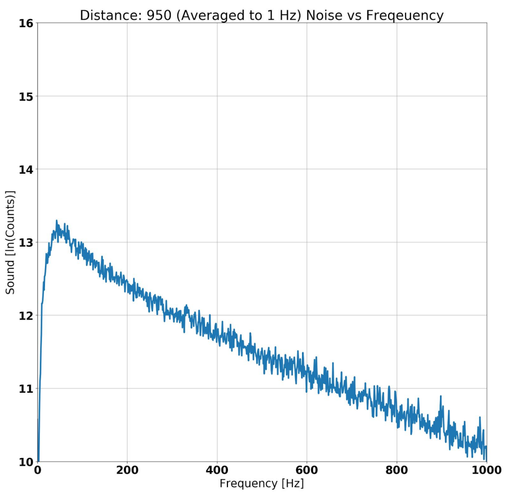
800 ft: Device A



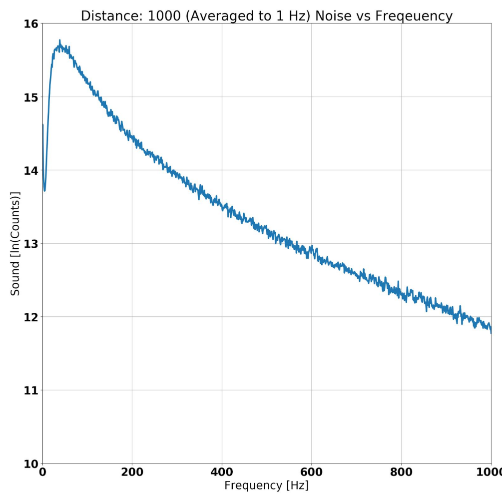
850 ft: Device B



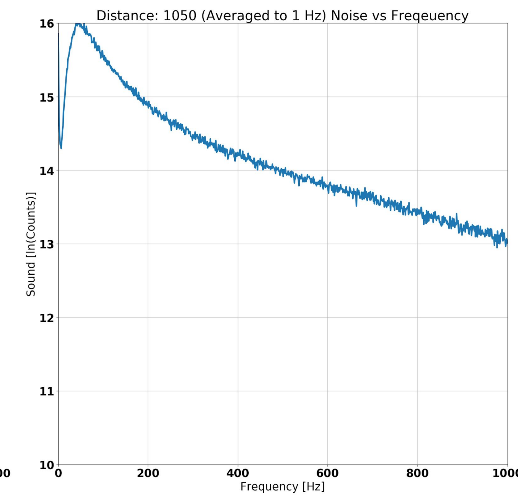
900 ft: Device C



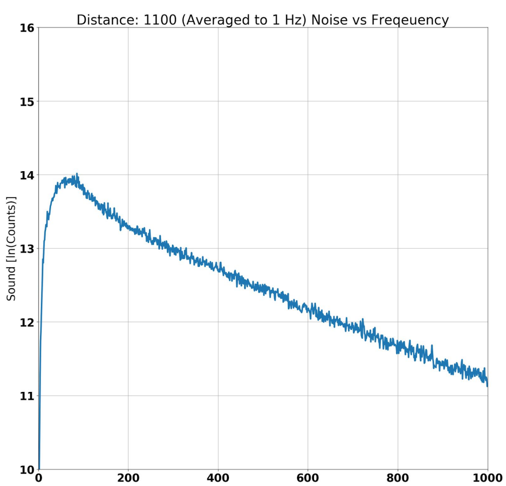
950 ft: Device A



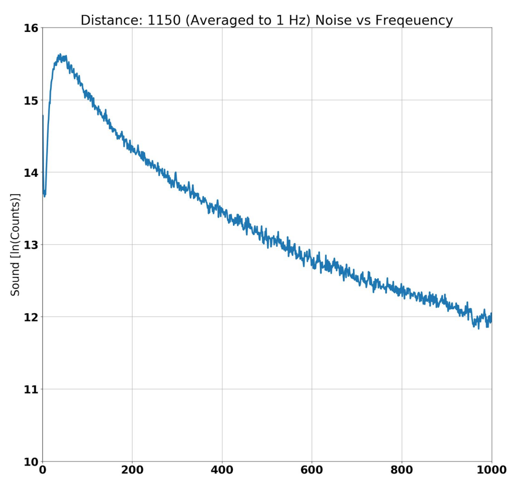
1000 ft: Device B



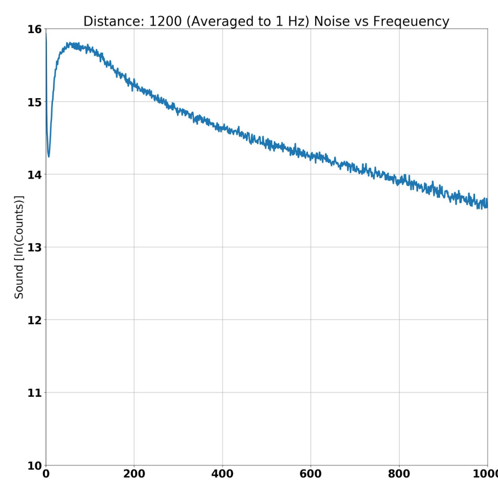
1050 ft: Device C



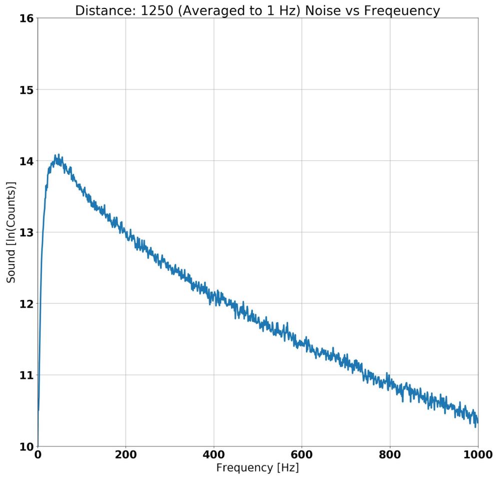
1100 ft: Device A



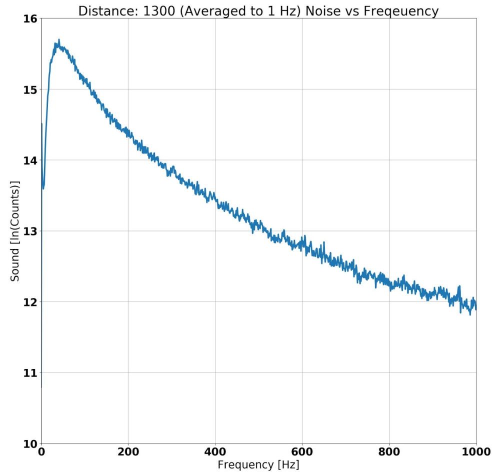
1150 ft: Device B



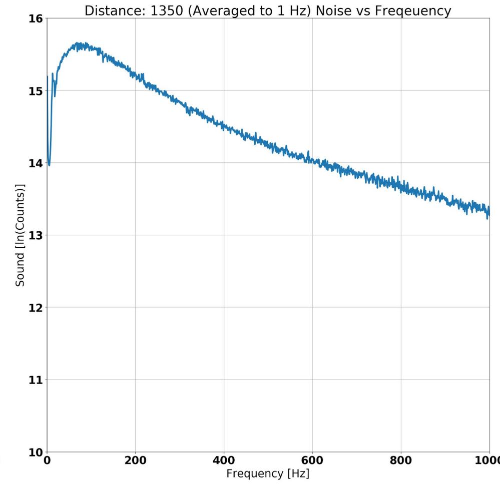
1200 ft: Device C



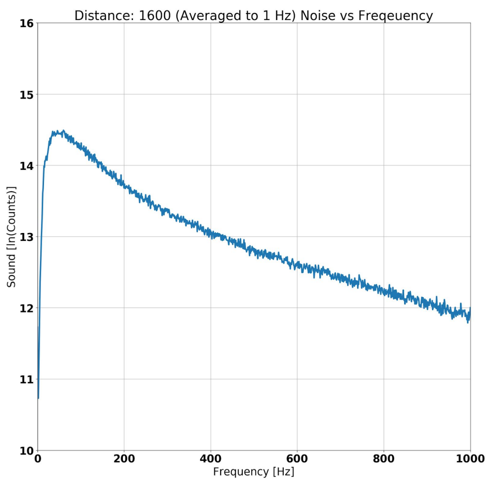
1250 ft: Device A



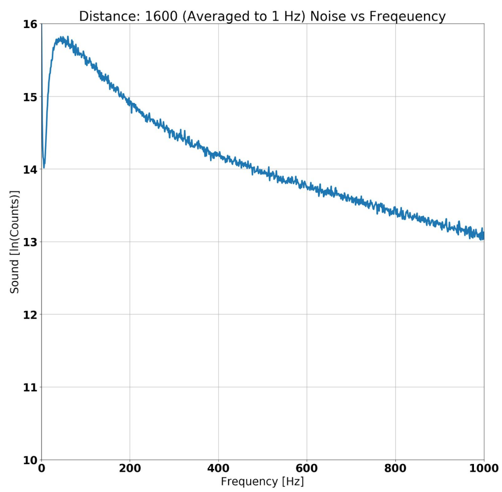
1300 ft: Device B



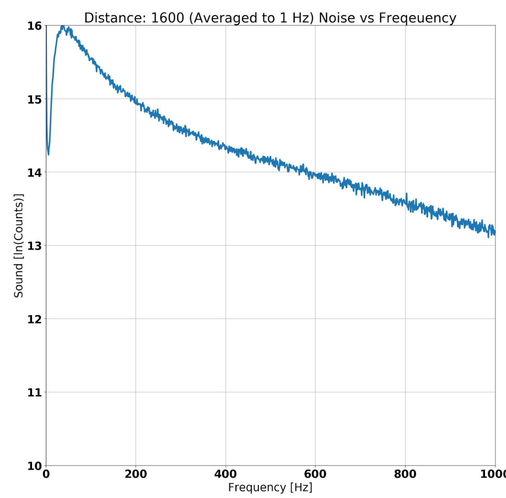
1350 ft: Device C



1600 ft: Device A



1600 ft: Device B



1600 ft: Device C

Analysis

I. Frequency of wind

The graphs of frequency vs sound counts for various distances shown in the results section do not have a pattern that would indicate the presence of a wind turbine. The frequency profiles are very similar for all of the distances. The data was recorded during a time when it was very windy, meaning that the majority of sound in the data is the sound of wind. This provides a lot of information on the properties of wind sound.

The frequency profile graphs peak at a frequency of around 50 Hz consistently across all devices and distances. The amount of noise detected by the microphone decreases as the frequency increases. This means that wind noise mostly occurs in the range of 50-100 Hz, but can also occur at higher frequencies. Unfortunately, the low frequency of wind makes it very hard to differentiate from the similar frequencies produced by the wind turbine. Figure 15 shows the sound count as a function of distance for different frequency ranges. All frequency ranges follow the same pattern as the distance increases, suggesting that wind is the only prevalent noise in the recordings.

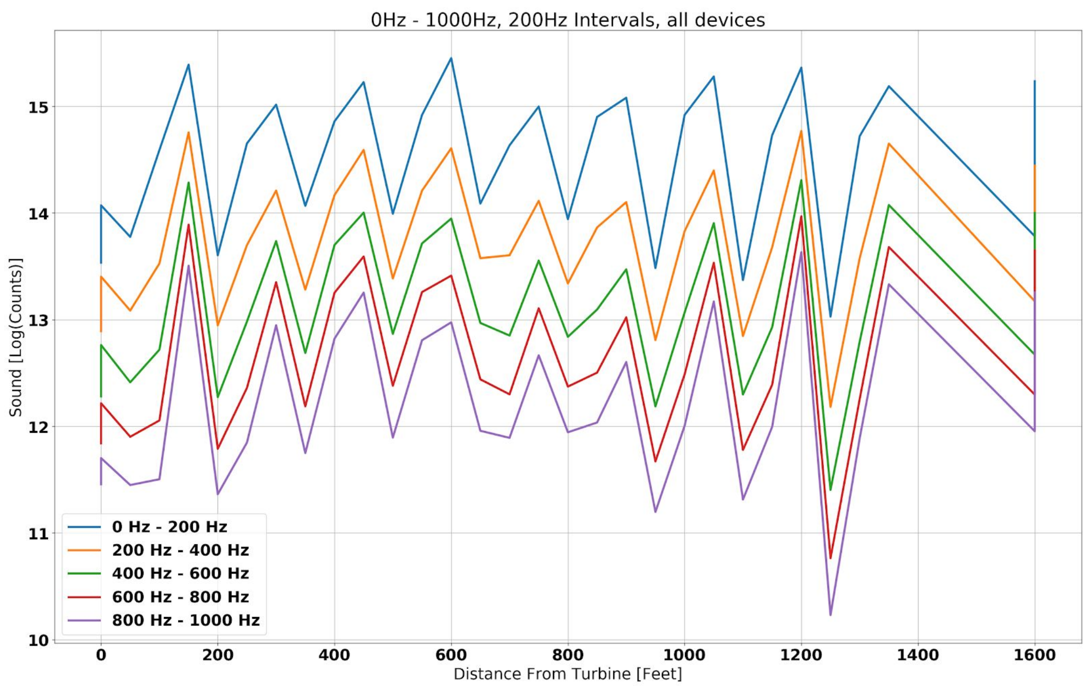


Figure 15: Distance vs. frequency graph for all devices, from 0 Hz to 1000 Hz.

II. Overlaid frequency trends

Frequency vs sound count for different distances were plotted on the same graph to compare the frequency profiles of simultaneous data points. Figure 16 shows the frequency profiles for 50, 100, and 150 feet, and figure 17 shows the frequency profiles for 200, 250, and 300 feet. It can be seen that the profiles for all of these data points follow the same trend regardless of the distance from the wind turbine. A wind turbine sound would appear as a spike at a certain frequency. The spike would be visible at different distances and would diminish as the distance increased. The consistency of the frequency profiles indicates that the microphones were not able to detect any sound from the wind turbine louder than plain wind.

In figures 16 and 17 it can be seen that the sound counts for the three distances are not the same. This is due to differences in how the gain of each microphone was set. Device C, represented in figures 16 and 17 by the green function, had the highest gain. Device B (orange) had the next highest gain, and device A (blue) had the lowest. Figure 18 shows the frequency profiles for different data points taken by the same device (device B). Because the gain for all of these recordings was the same, there is not a significant difference in sound counts between the different data points.

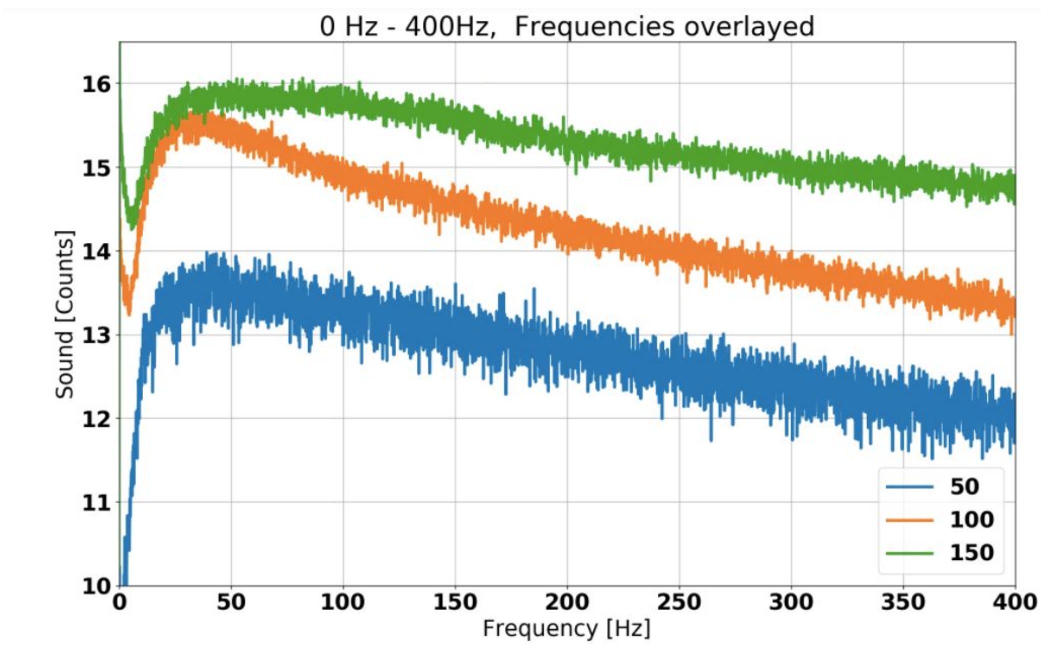


Figure 16: Overlaid frequency profiles for 50, 100, and 150 feet.

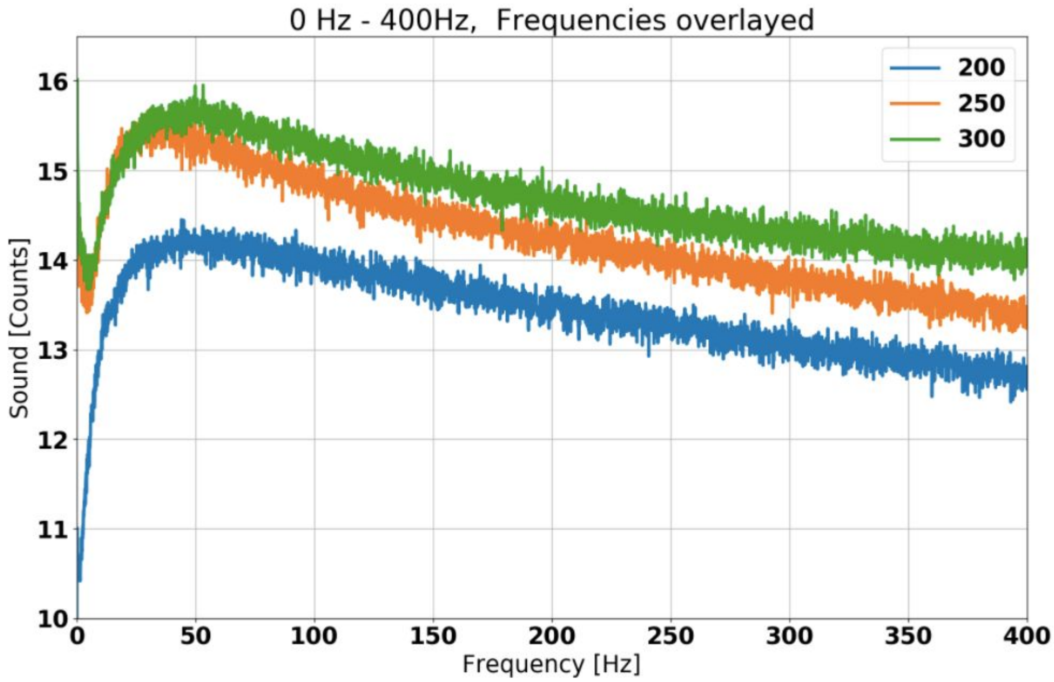


Figure 17: Overlaid frequency profiles for 200, 250, and 300 feet.

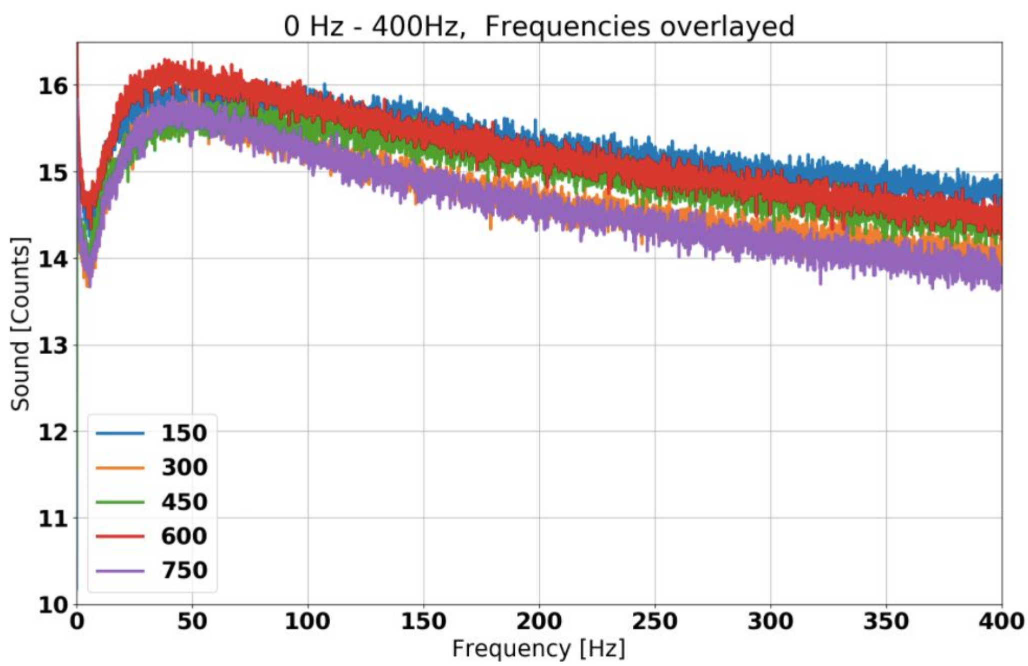


Figure 18: Overlaid frequency profiles for device B. 150 - 750 feet.

III. Spectrograms

The spectrograms plotted frequency vs time for certain distances. The lighter colors correspond to higher sound counts and the darker colors correspond to lower sound counts. Trends that could indicate the presence of a wind turbine include frequency peaks that are consistent over time and frequencies that peak at regular time intervals. A frequency peak consistent over time would appear as a line of a lighter color across the graph. Frequency peaks at regular time intervals would appear as small oscillations between lighter and darker colors within a certain frequency range. The spectrograms were plotted in small time and frequency intervals so that these oscillations could be detected. Even with this level of accuracy, no indications of a wind turbine were found. There are large fluctuations in the data that do not happen in regular time intervals. These are likely due to changes in wind speed and are not caused by the noise from a wind turbine.

The spectrogram data varies between the three different devices, even when recording at the same time. Simultaneous recordings at 0 feet and at 1600 feet are shown in figures 19-50 below. The sound counts from the data taken by device C are generally much higher than those taken by device B and device A because gain from the microphone of device C was higher during recording.

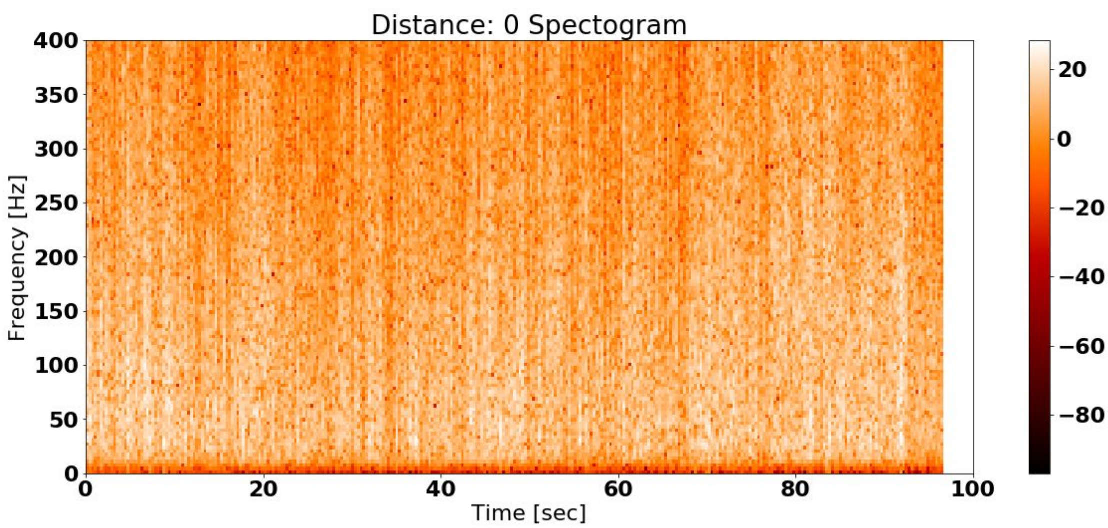


Figure 19: Spectrogram for device A at 0 feet from the turbine.

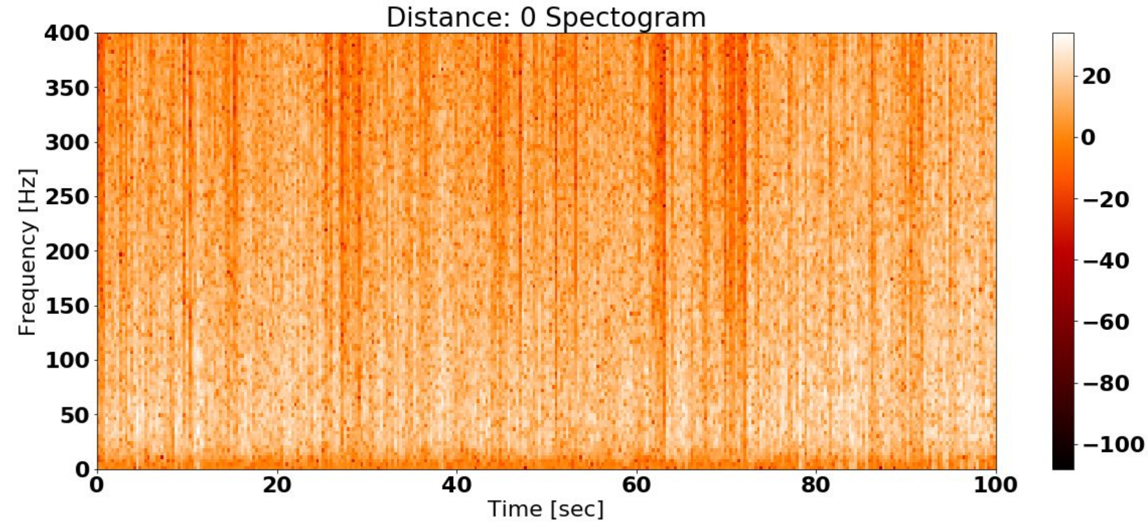


Figure 20: Spectrogram for device B at 0 feet from the turbine.

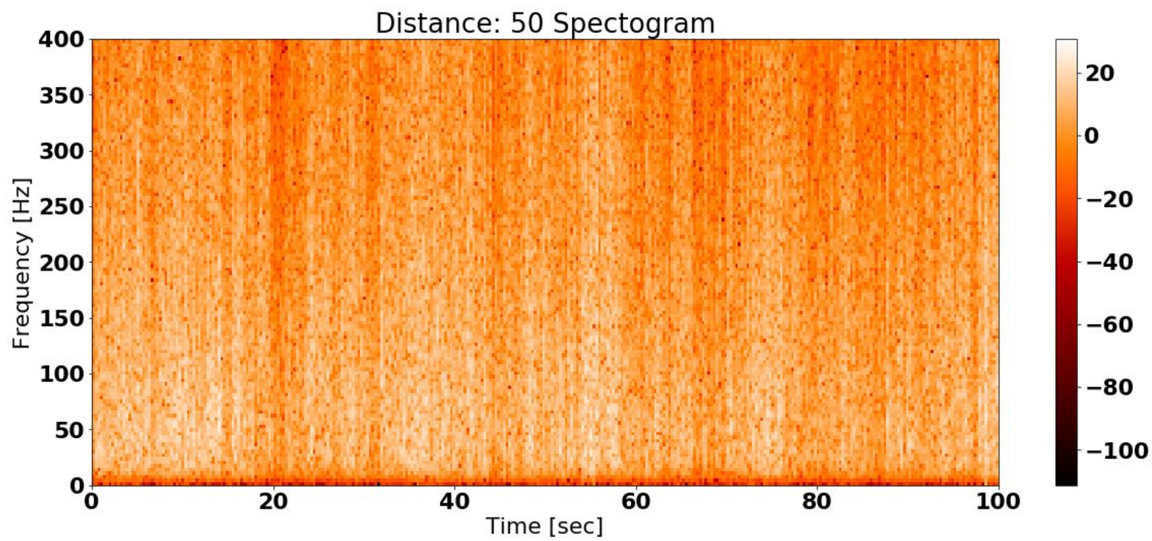


Figure 21: Spectrogram for device A at 50 feet from the turbine.

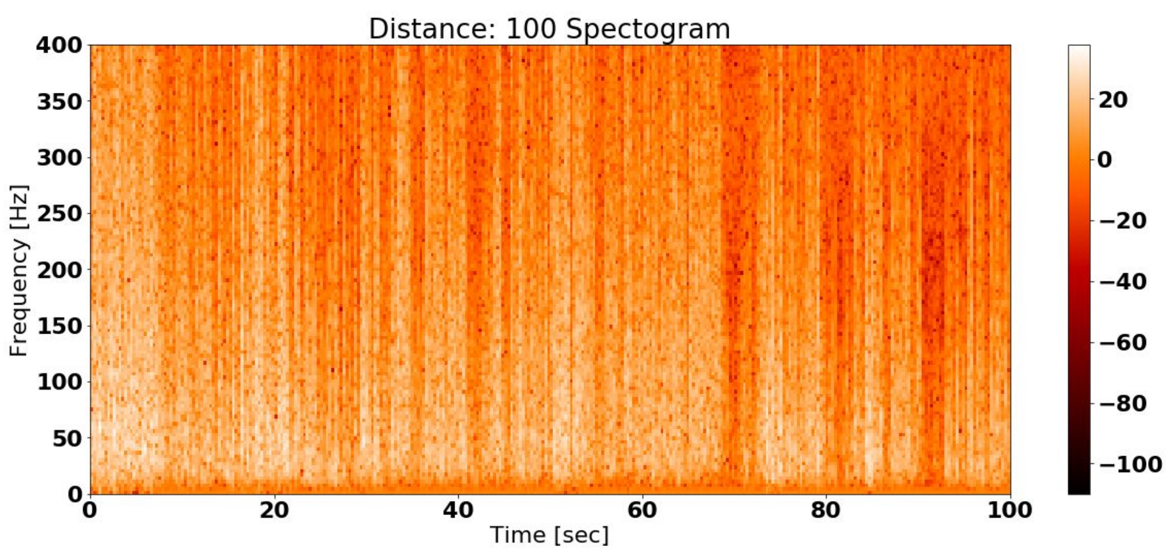


Figure 22: Spectrogram for device B at 100 feet from the turbine.

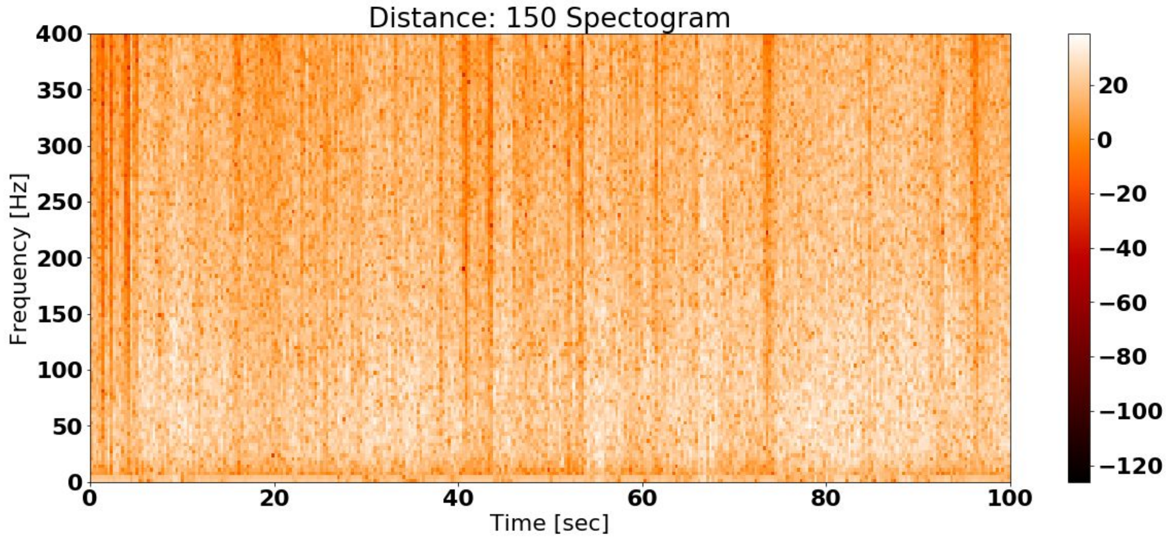


Figure 23: Spectrogram for device C at 150 feet from the turbine.

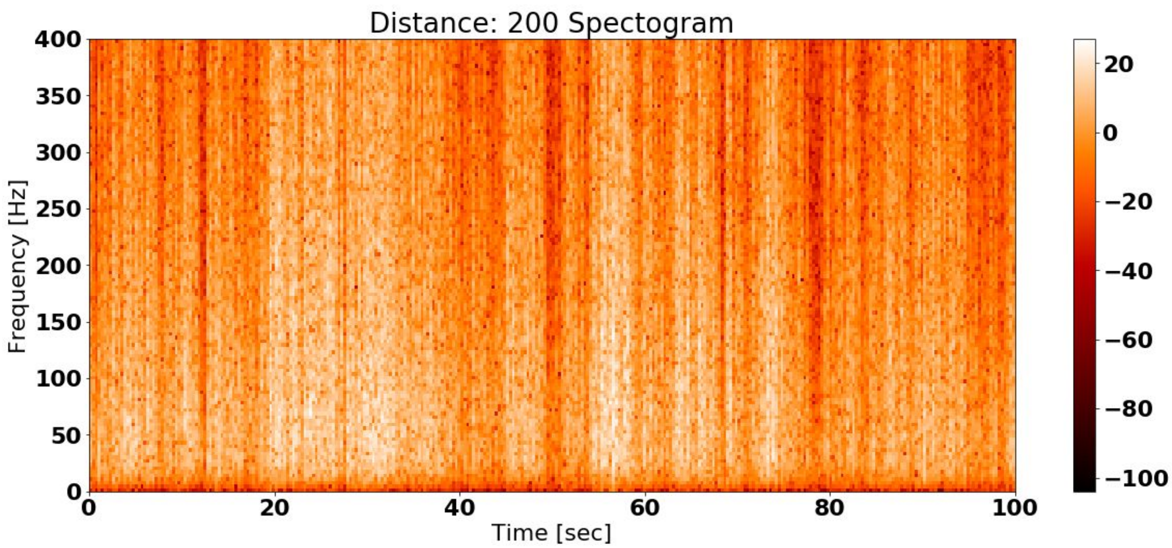


Figure 24: Spectrogram for device A at 200 feet from the turbine.

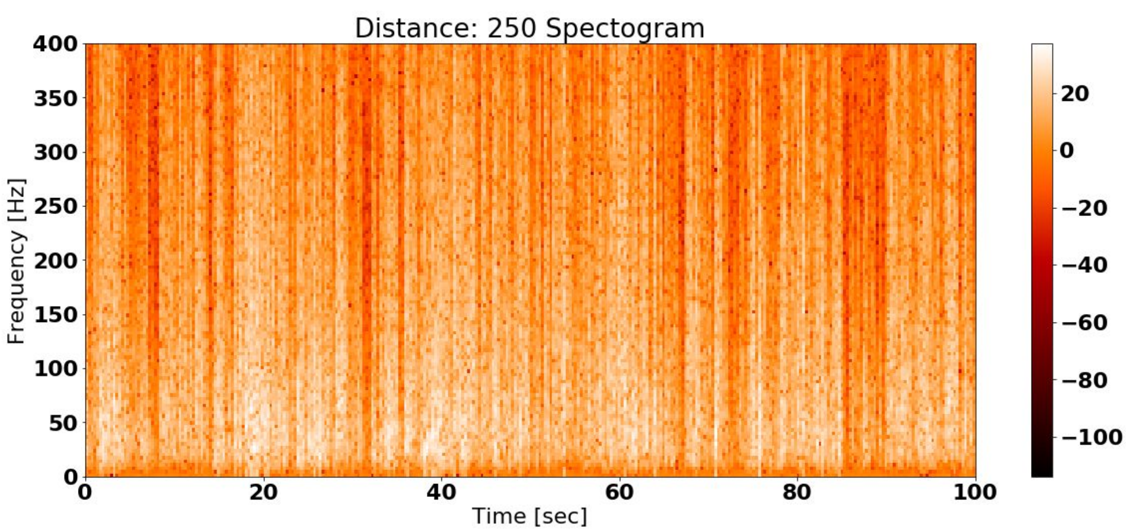


Figure 25: Spectrogram for device B at 250 feet from the turbine.

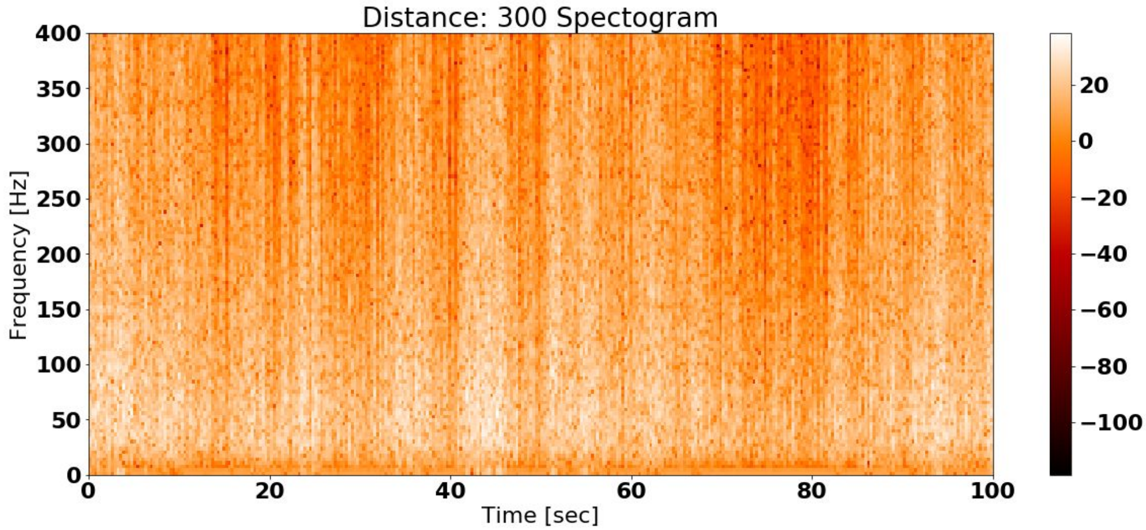


Figure 26: Spectrogram for device C at 300 feet from the turbine.

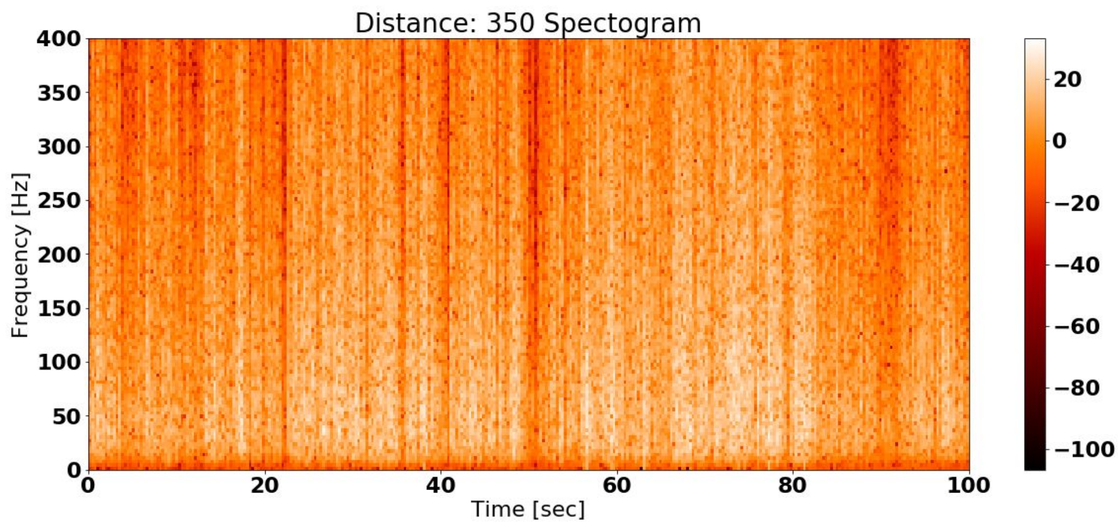


Figure 27: Spectrogram for device A at 350 feet from the turbine.

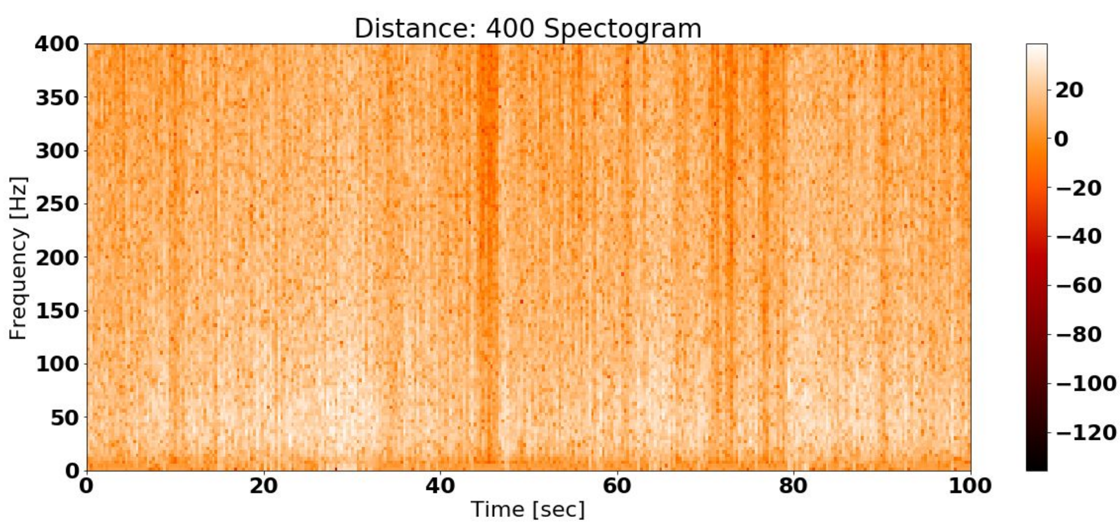


Figure 28: Spectrogram for device B at 400 feet from the turbine.

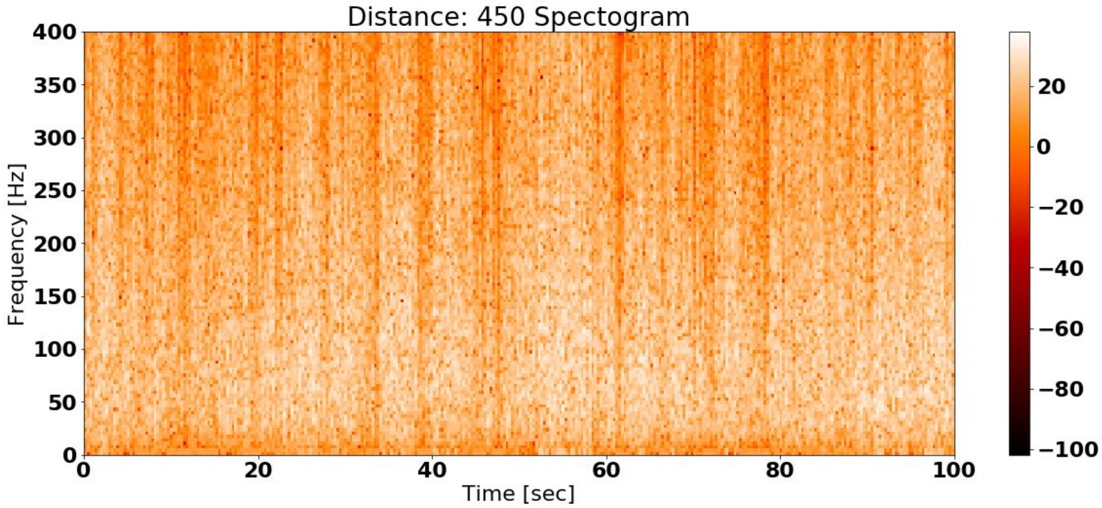


Figure 29: Spectrogram for device C at 450 feet from the turbine.

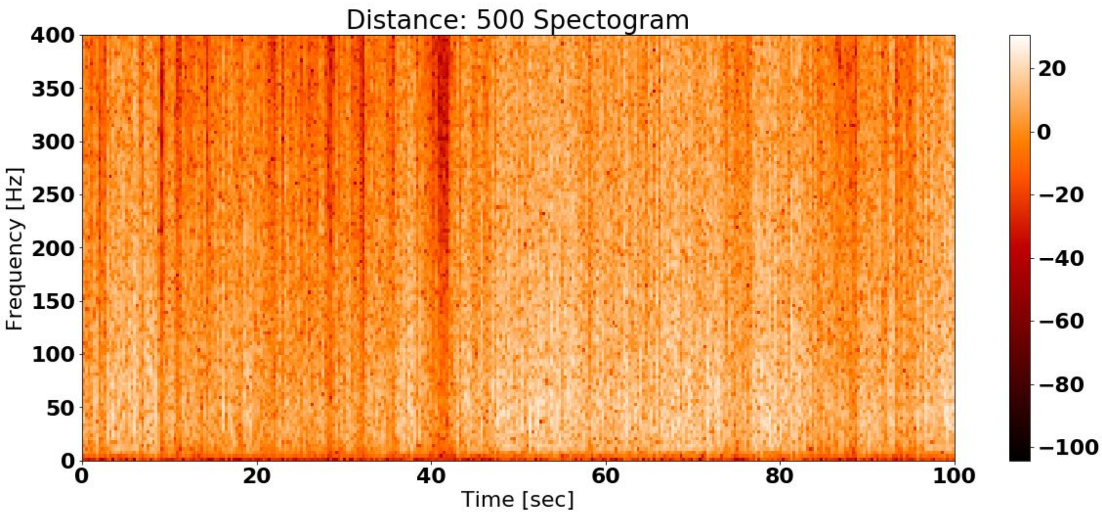


Figure 30: Spectrogram for device A at 500 feet from the turbine.

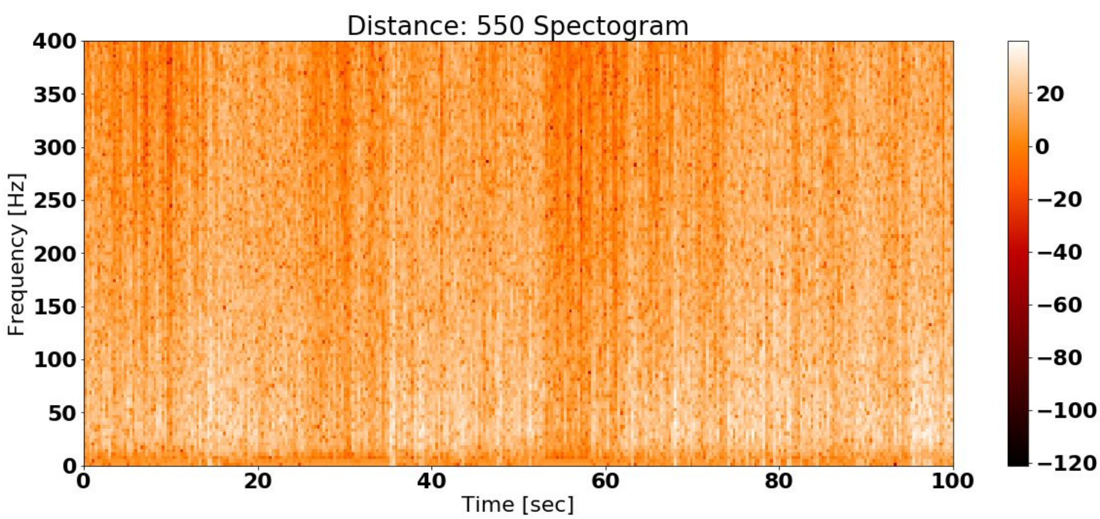


Figure 31: Spectrogram for device B at 550 feet from the turbine.

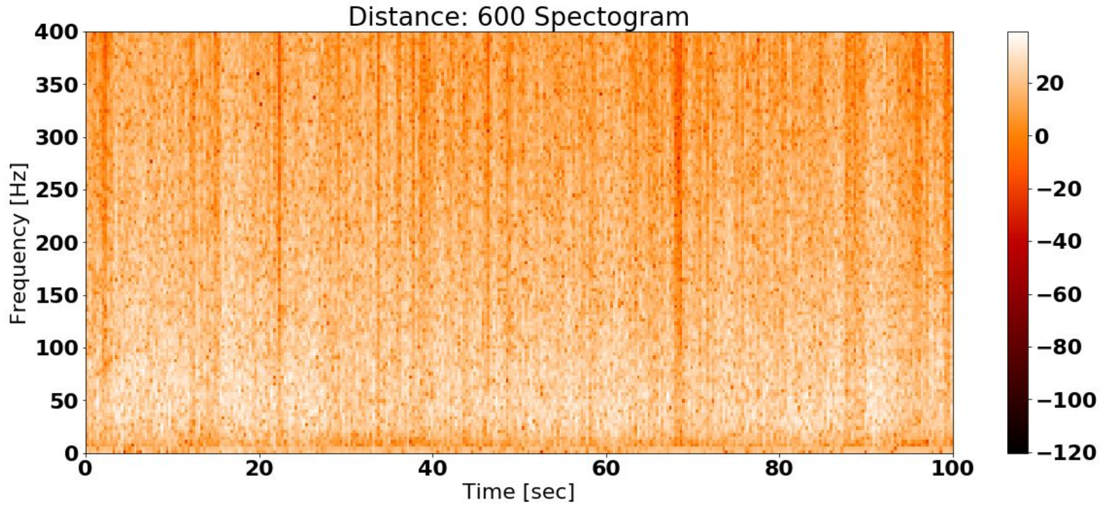


Figure 32: Spectrogram for device C at 600 feet from the turbine.

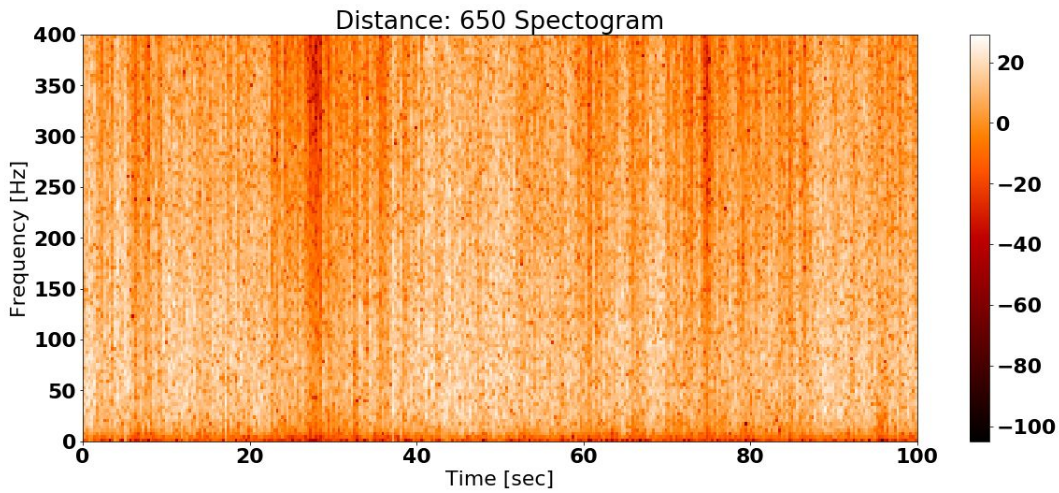


Figure 33: Spectrogram for device B at 650 feet from the turbine

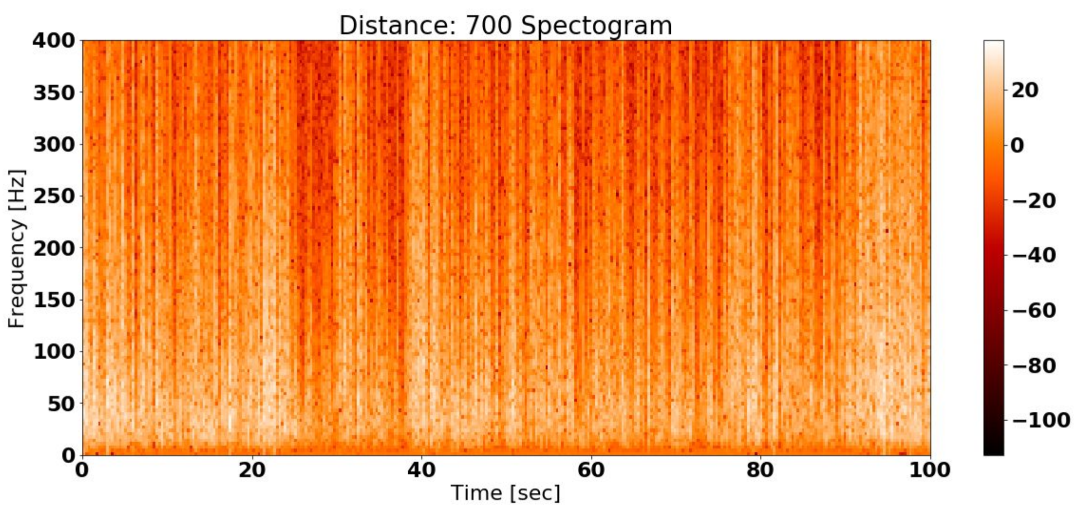


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Figure 34: Spectrogram for device B at 700 feet from the turbine

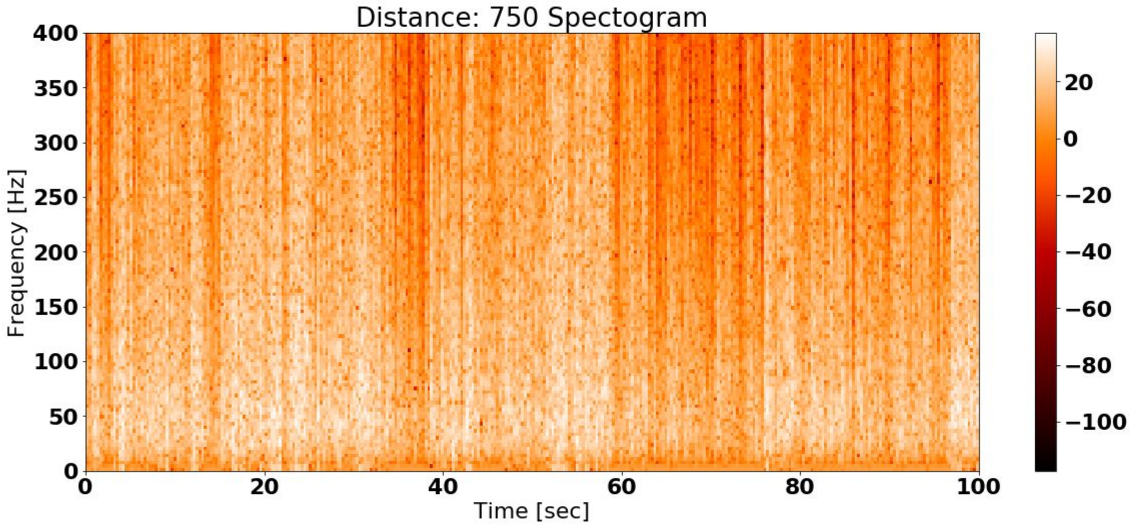


Figure 35: Spectrogram for device C at 750 feet from the turbine.

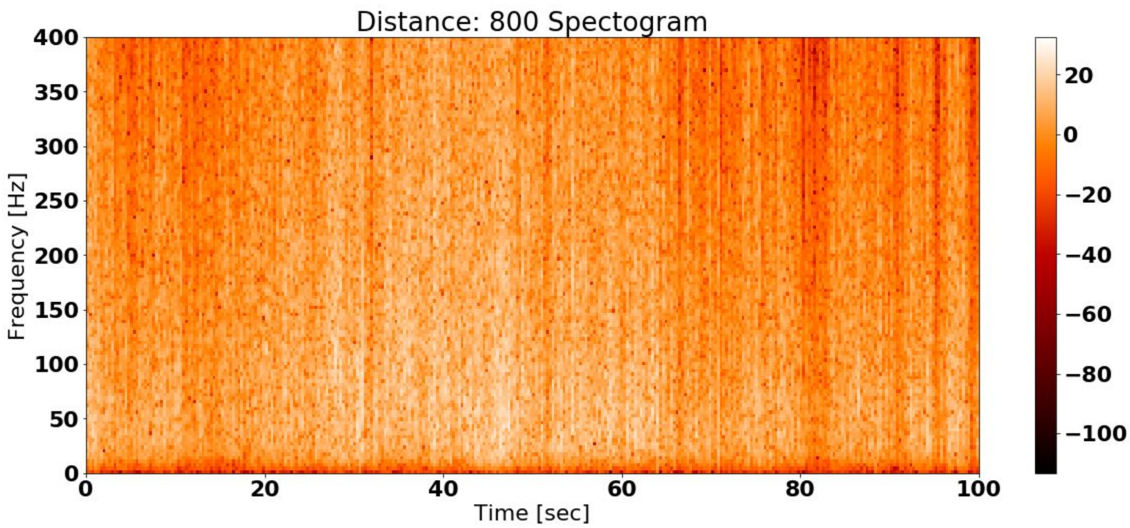


Figure 36: Spectrogram for device A at 800 feet from the turbine

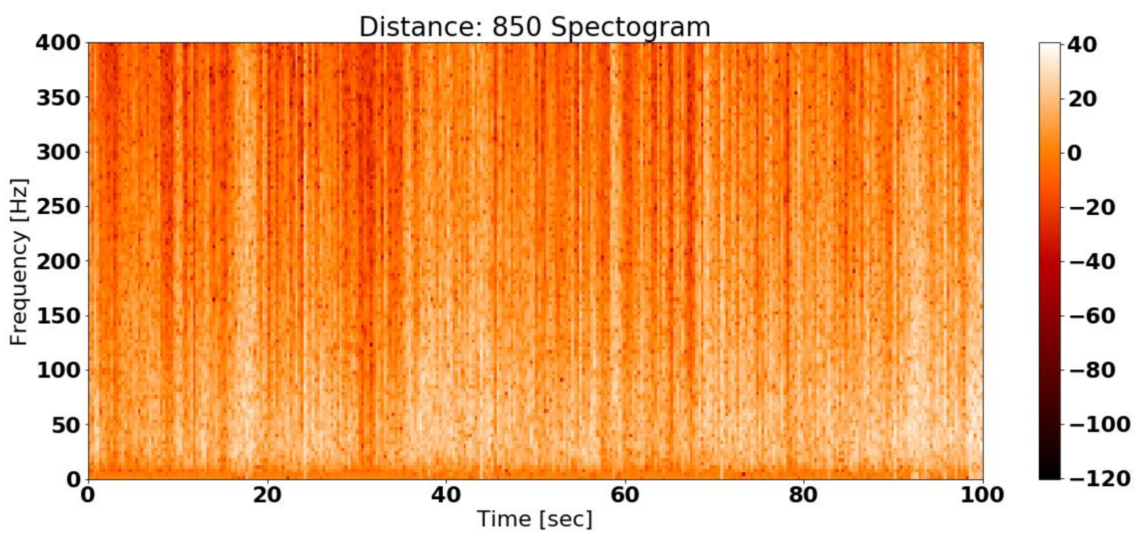


Figure 37: Spectrogram for device B at 850 feet from the turbine

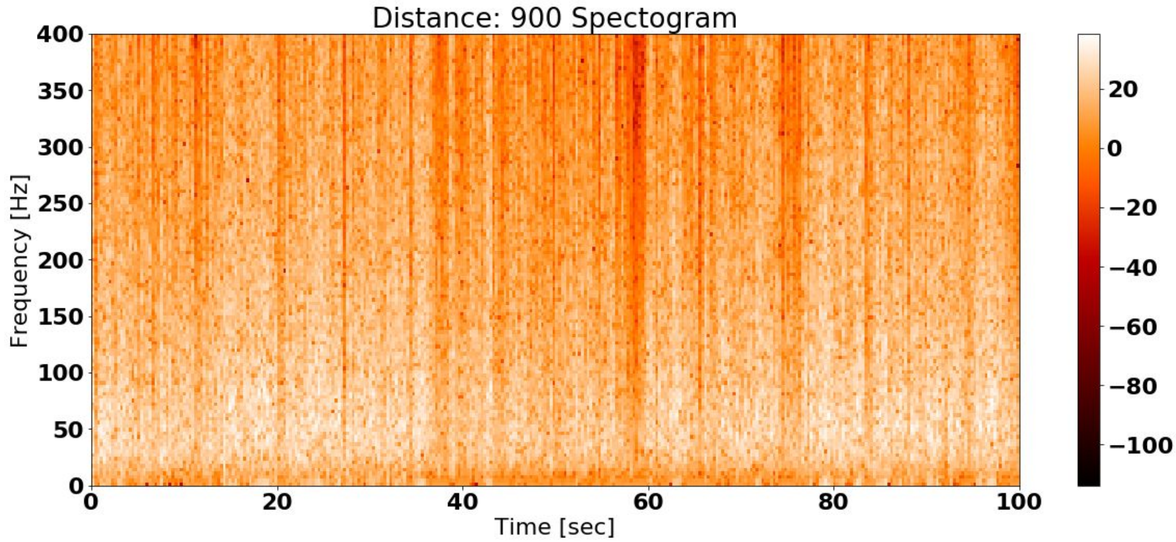


Figure 38: Spectrogram for device C at 900 feet from the turbine

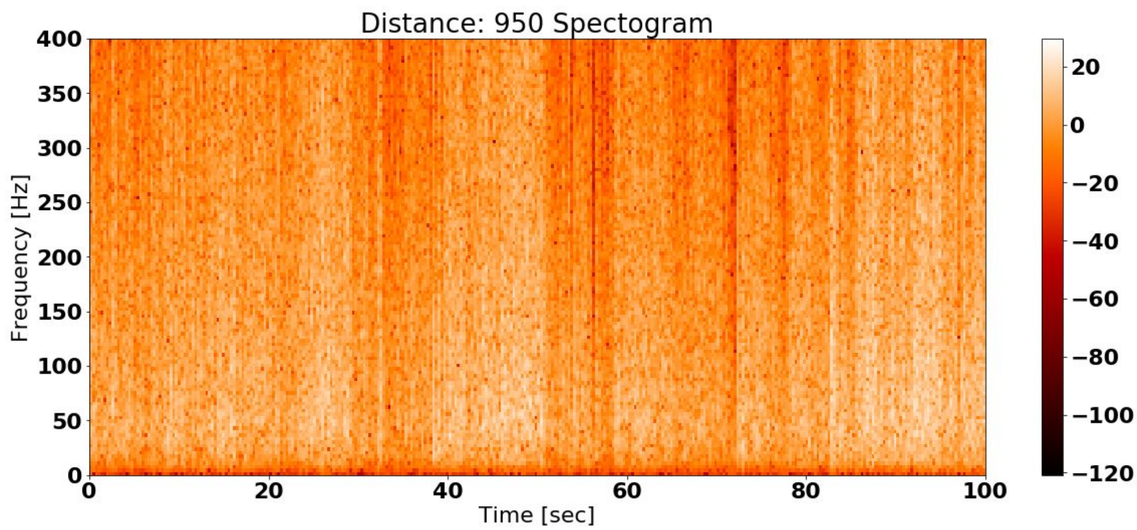


Figure 39: Spectrogram for device A at 950 feet from the turbine

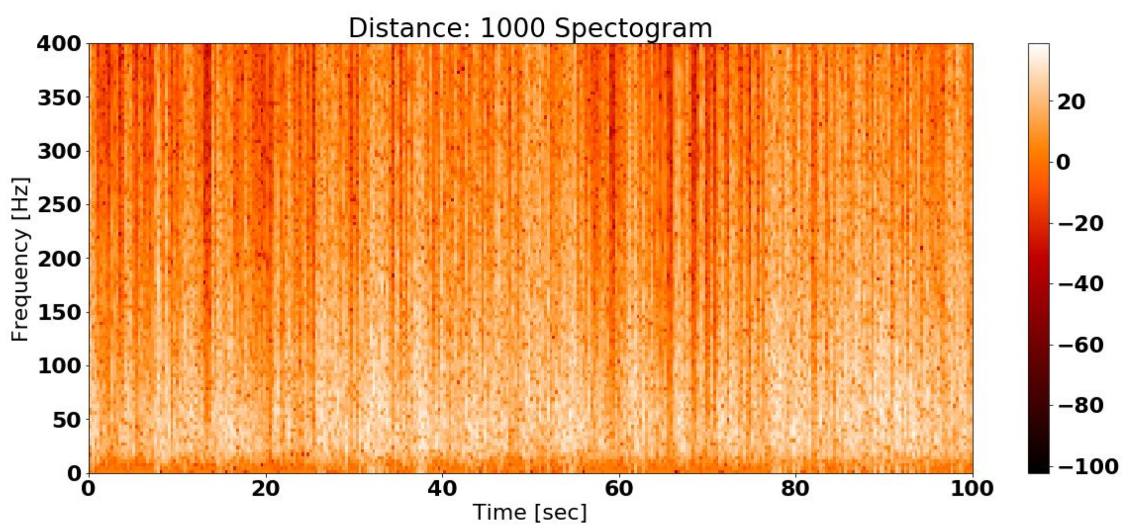


Figure 40: Spectrogram for device B at 1000 feet from the turbine

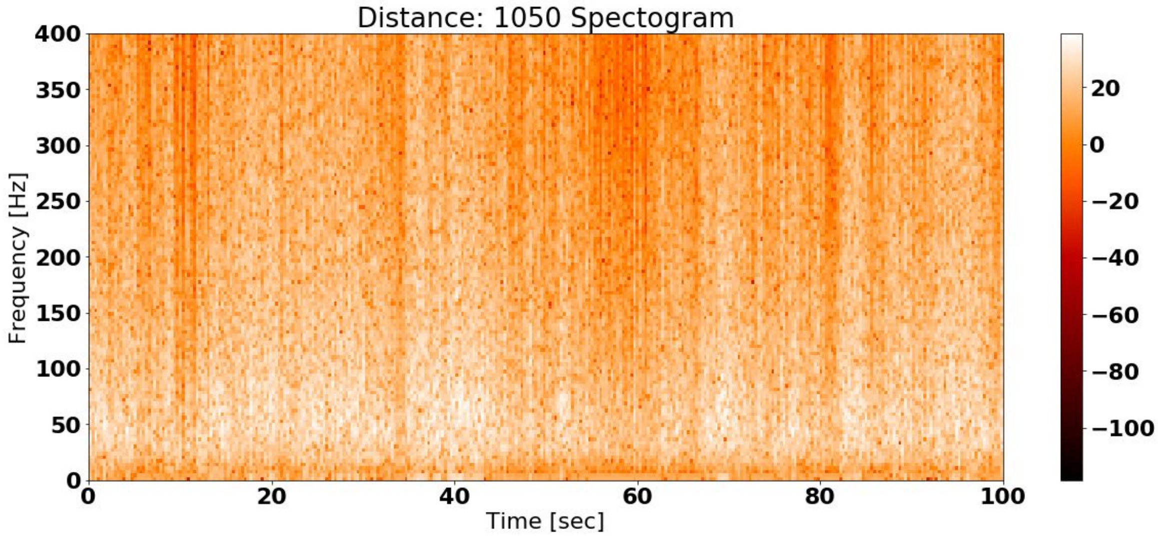


Figure 41: Spectrogram for device C at 1050 feet from the turbine

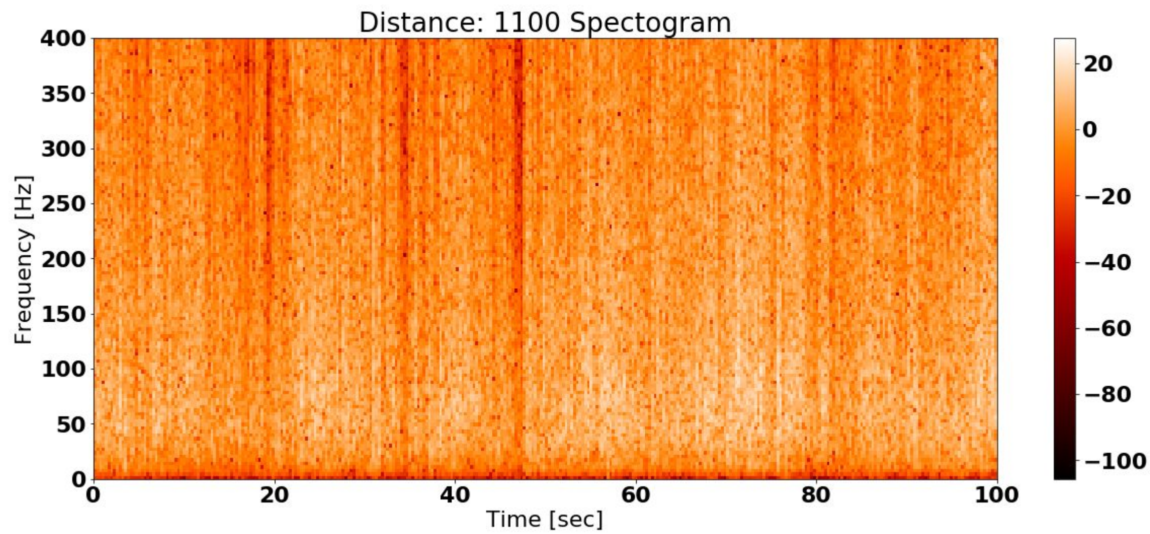


Figure 42: Spectrogram for device A at 1100 feet from the turbine

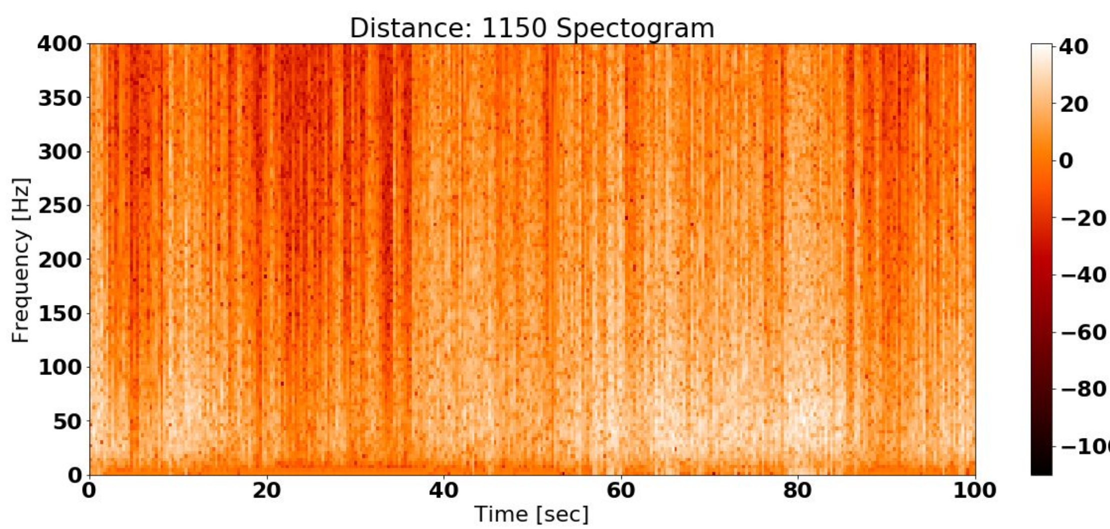


Figure 43: Spectrogram for device B at 1150 feet from the turbine

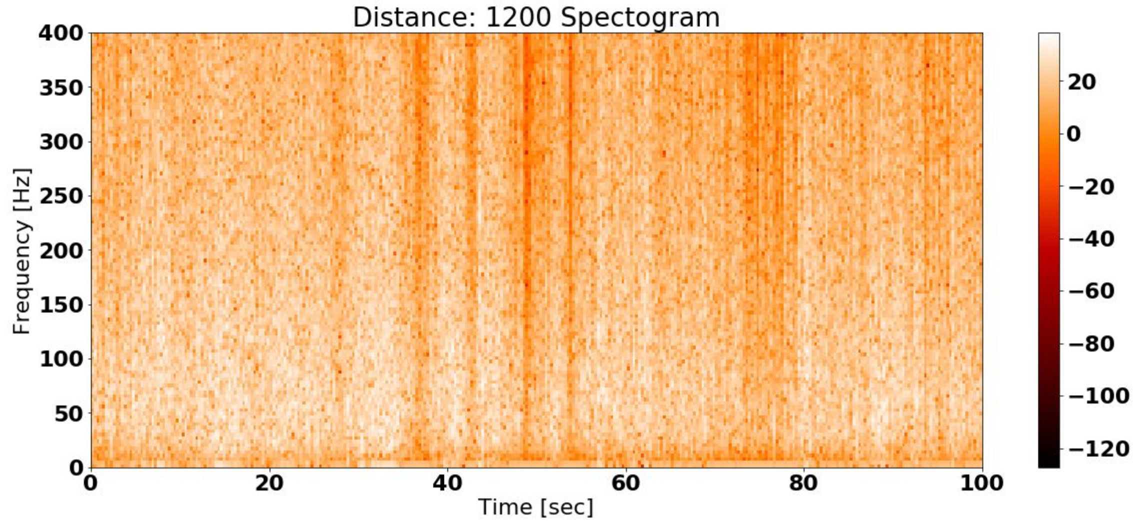


Figure 44: Spectrogram for device C at 1200 feet from the turbine

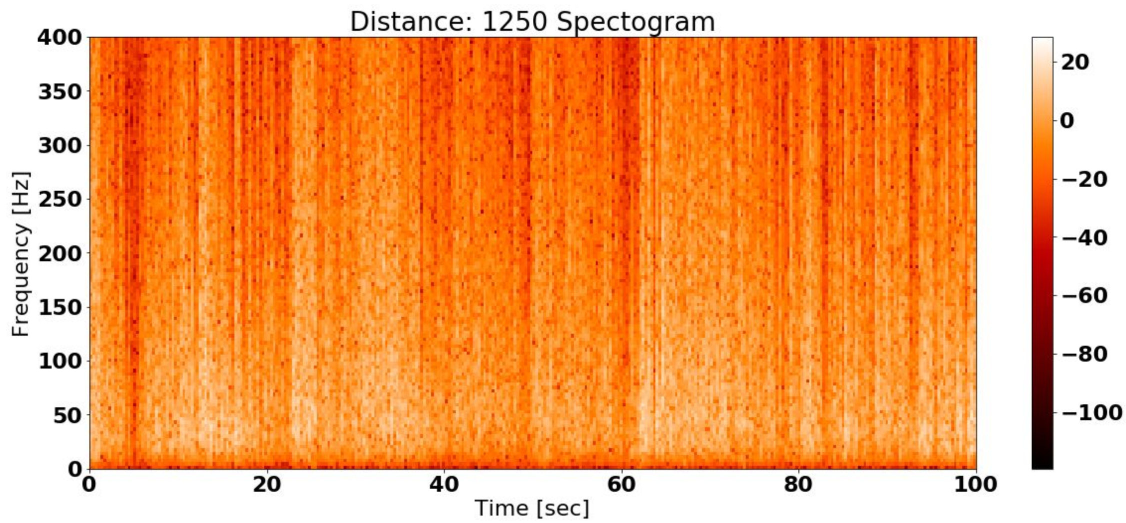


Figure 45: Spectrogram for device A at 1250 feet from the turbine

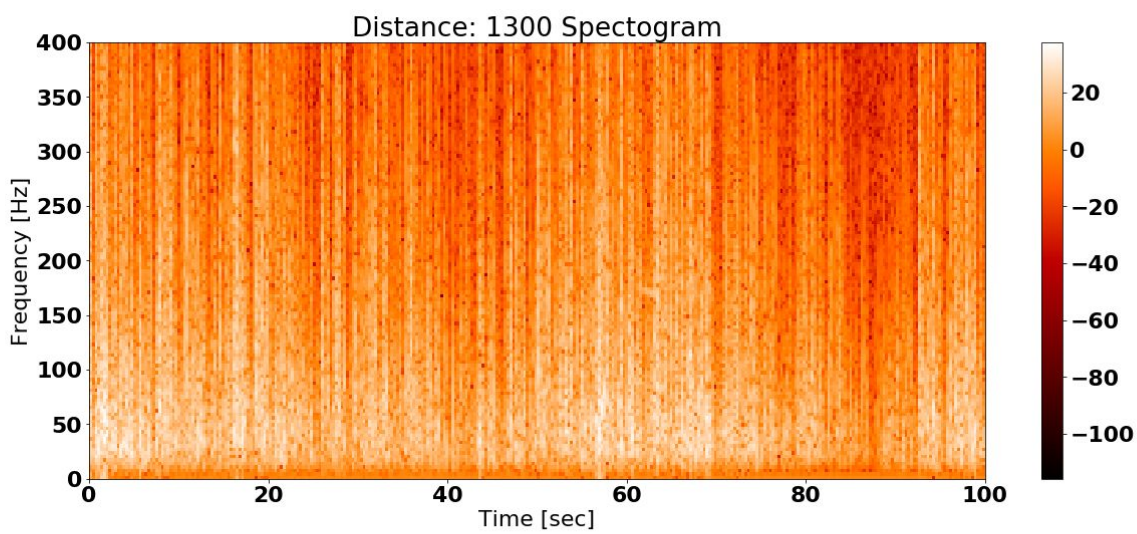


Figure 46: Spectrogram for device B at 1300 feet from the turbine

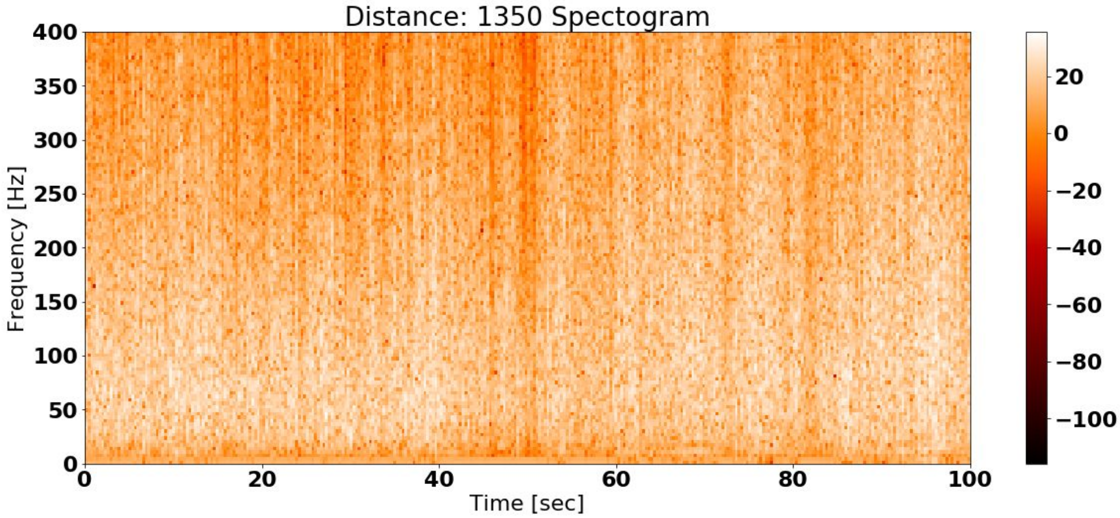


Figure 47: Spectrogram for device C at 1350 feet from the turbine

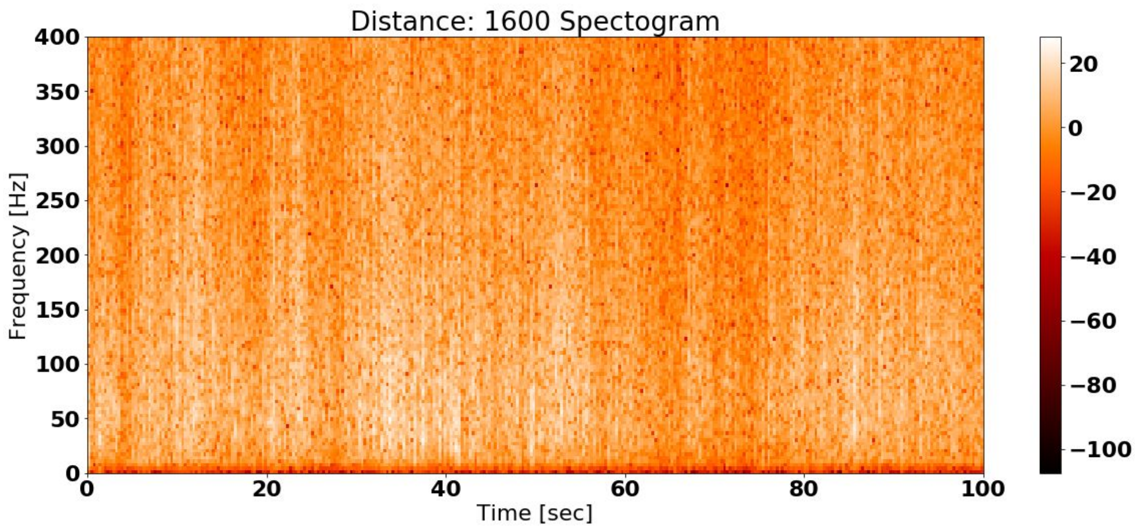


Figure 48: Spectrogram for device A at 1600 feet from the turbine.

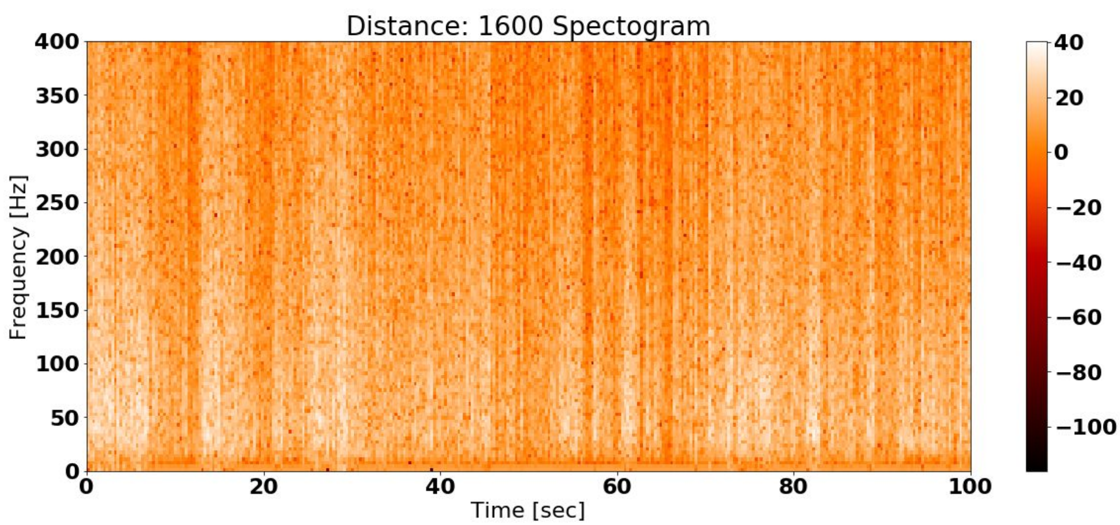


Figure 49: Spectrogram for device B at 1600 feet from the turbine.

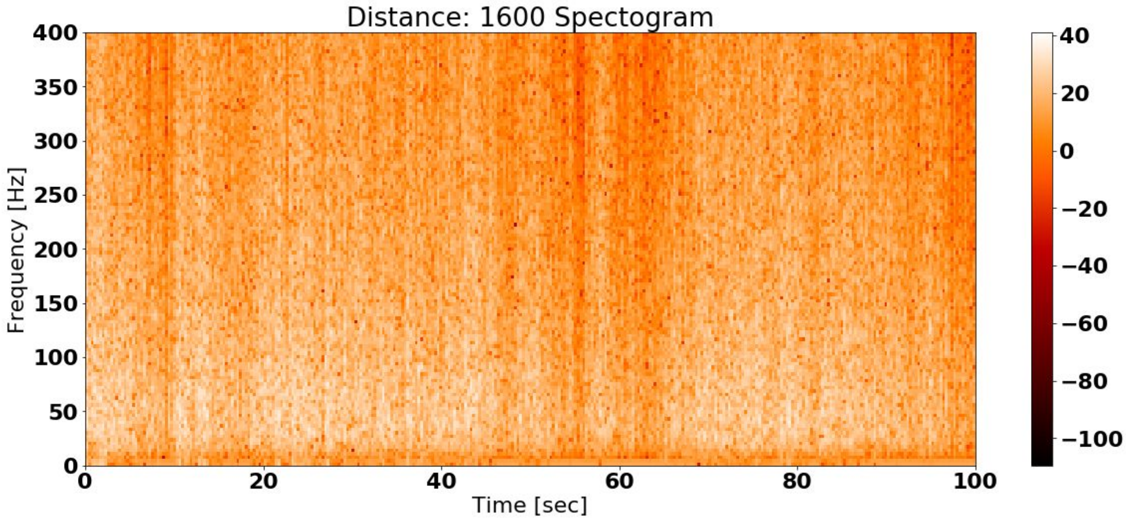


Figure 50: Spectrogram for device C at 1600 feet from the turbine.

IV. Trends in distance from the wind turbine

In order to see how the amount of sound of certain frequencies changed as the distance from the wind turbine increased, a plot of sound count vs distance for various frequencies was made. First, a wider range of frequencies were investigated to see if there was a general trend arising as the distance from the wind turbine increases. Figure 51 shows the data for all three devices as a function of distance. If a wind turbine was present, a decrease in sound for the lower frequency ranges such as 0 Hz - 200 Hz would be expected. This trend is not seen in figure 51.

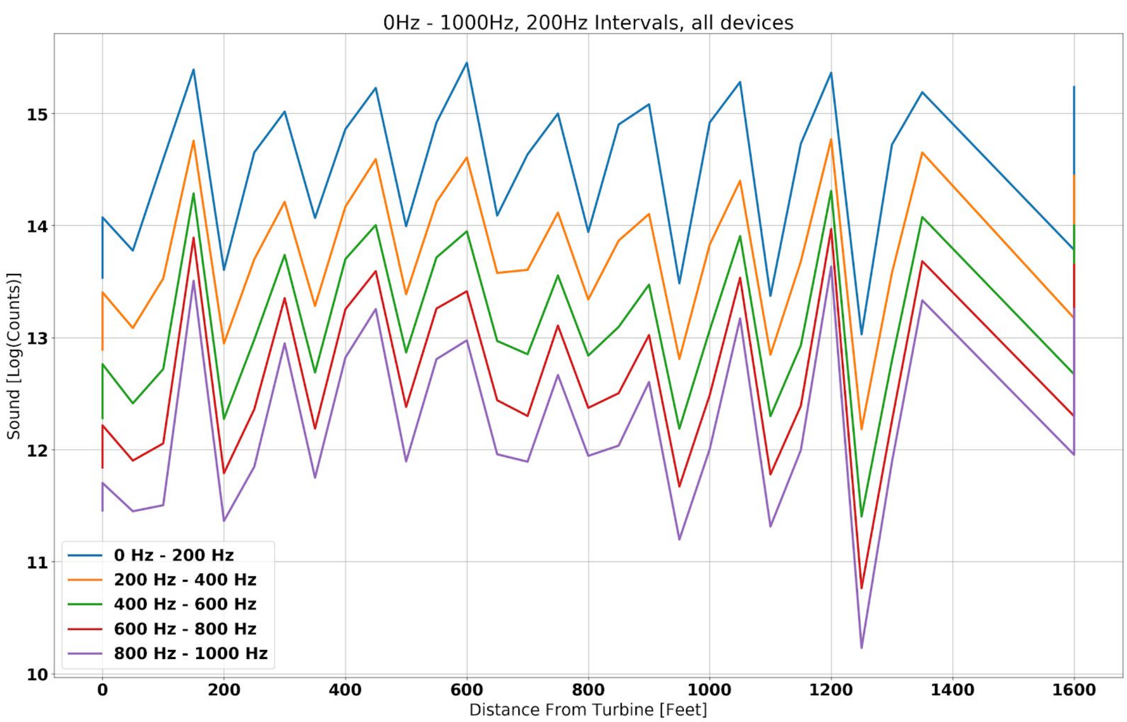


Figure 51: Sound at each distance from all three devices at 0 Hz to 1000 Hz.

Because the gain in the three microphones was not calibrated, the graphs of sound count vs distance were separated for each of the three devices. Figures 52, 53, and 54 show sound at each location for each device. These graphs show a similar trend, which confirms that the devices record the same sounds at about the same time and distance. For devices A and B, there is an increase in general noise from 0 feet to 500 feet and a decrease from 500 feet to 1200 feet. This could be a trend that indicates noise coming from a wind turbine. But the higher sound counts in 1600 feet does not support the same conclusion.

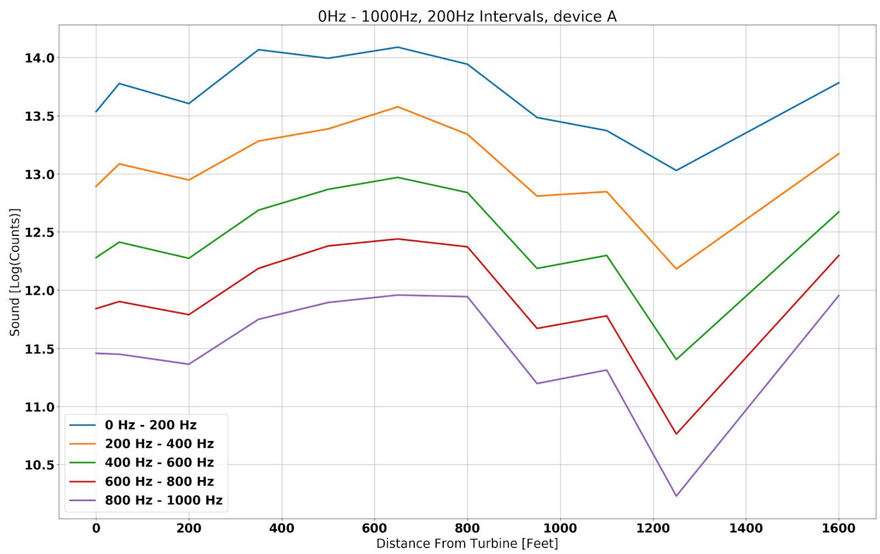


Figure 52: Sound at each distance from device A at 0 Hz to 1000 Hz.

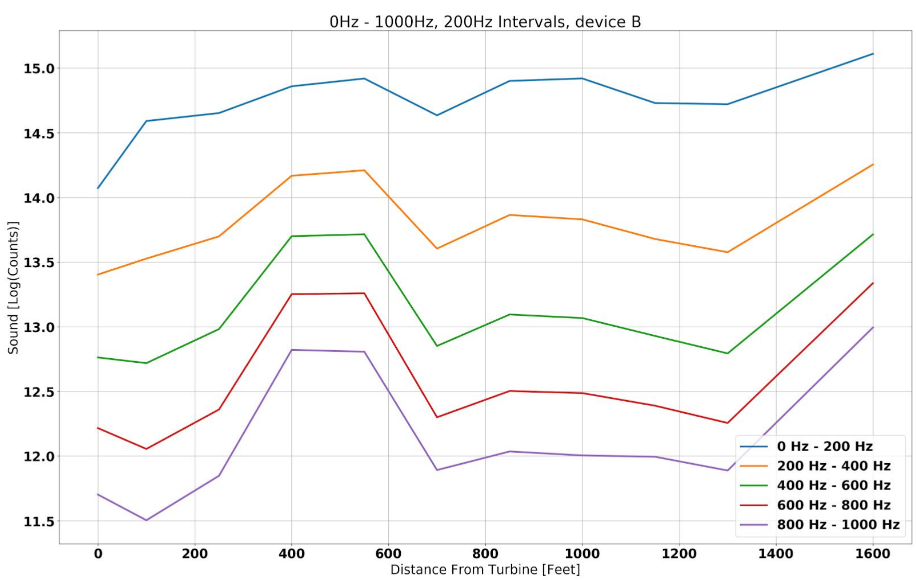


Figure 53: Sound at each distance from device B at 0 Hz to 1000 Hz.

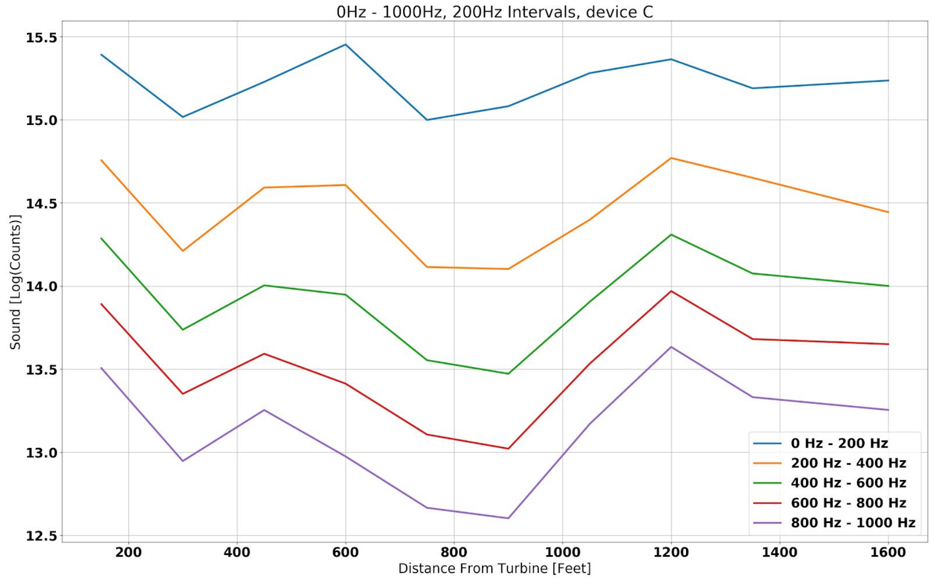


Figure 54: Sound at each distance from device C at 0 Hz to 1000 Hz.

Because wind turbines produce noise at low frequencies, figures 55, 56, and 57 show frequency ranges only up to 500 Hz. Each line represents a frequency range of 100 Hz. For the data points from device A (figure 55) and device C (figure 57), All of the lines seem to follow the same trend, except for the 0-100Hz line. The 0-100Hz frequency range is where the sound from a wind turbine would be expected to be found. The unique pattern of this line could be an indication of a wind turbine. However, the different trend does not occur for device B, and the amount of sound does not decrease for data points far away from the turbine. The different trend is likely due to the fact that most wind occurs in this frequency range and can be a source of disorder.

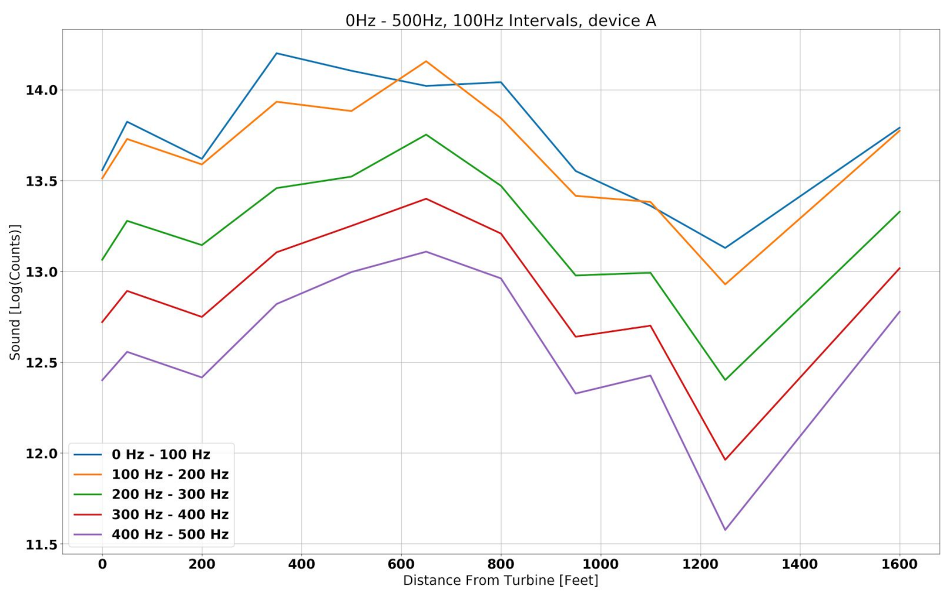


Figure 55: Sound at each distance from device A at 0 Hz to 500 Hz.

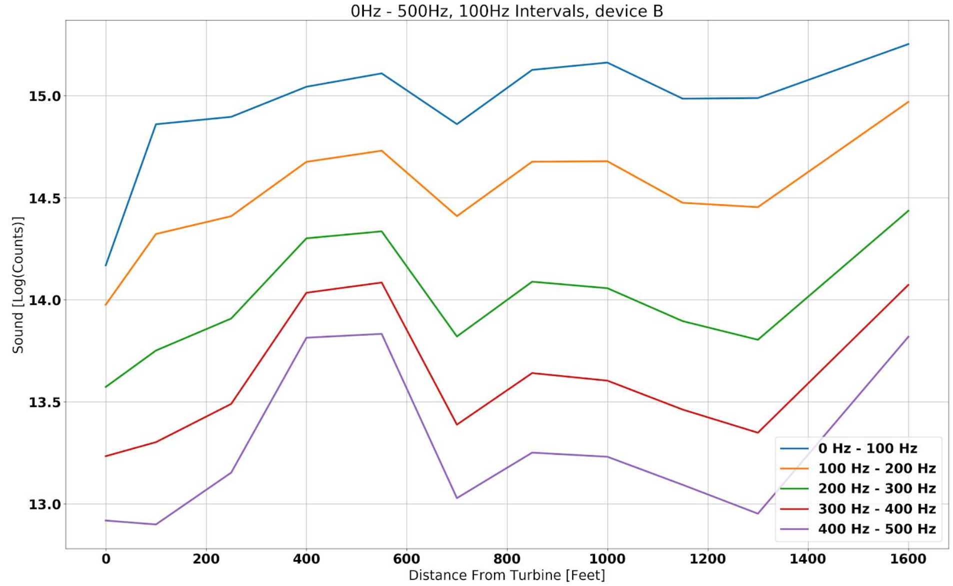


Figure 56: Sound at each distance from device B at 0 Hz to 500 Hz.

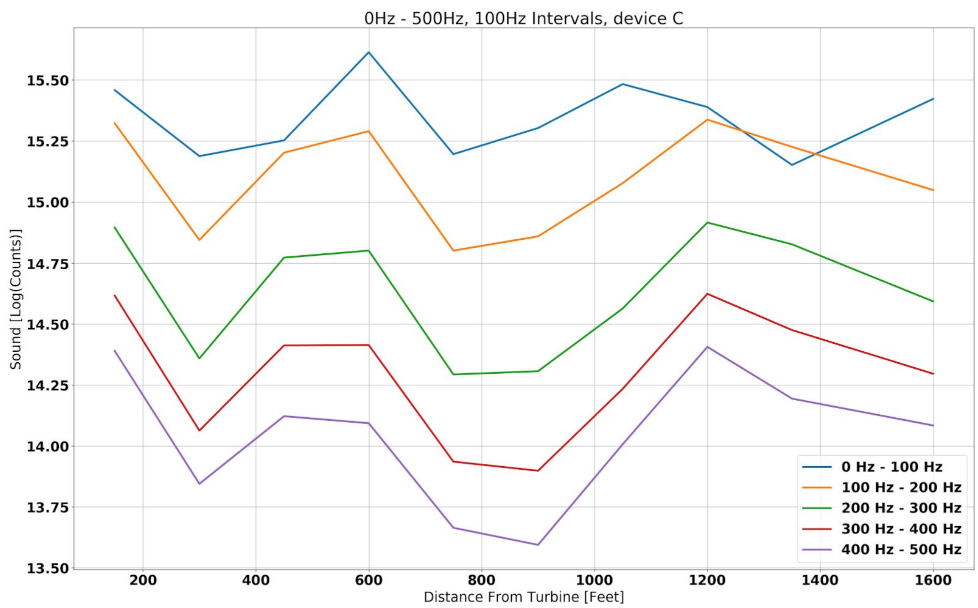
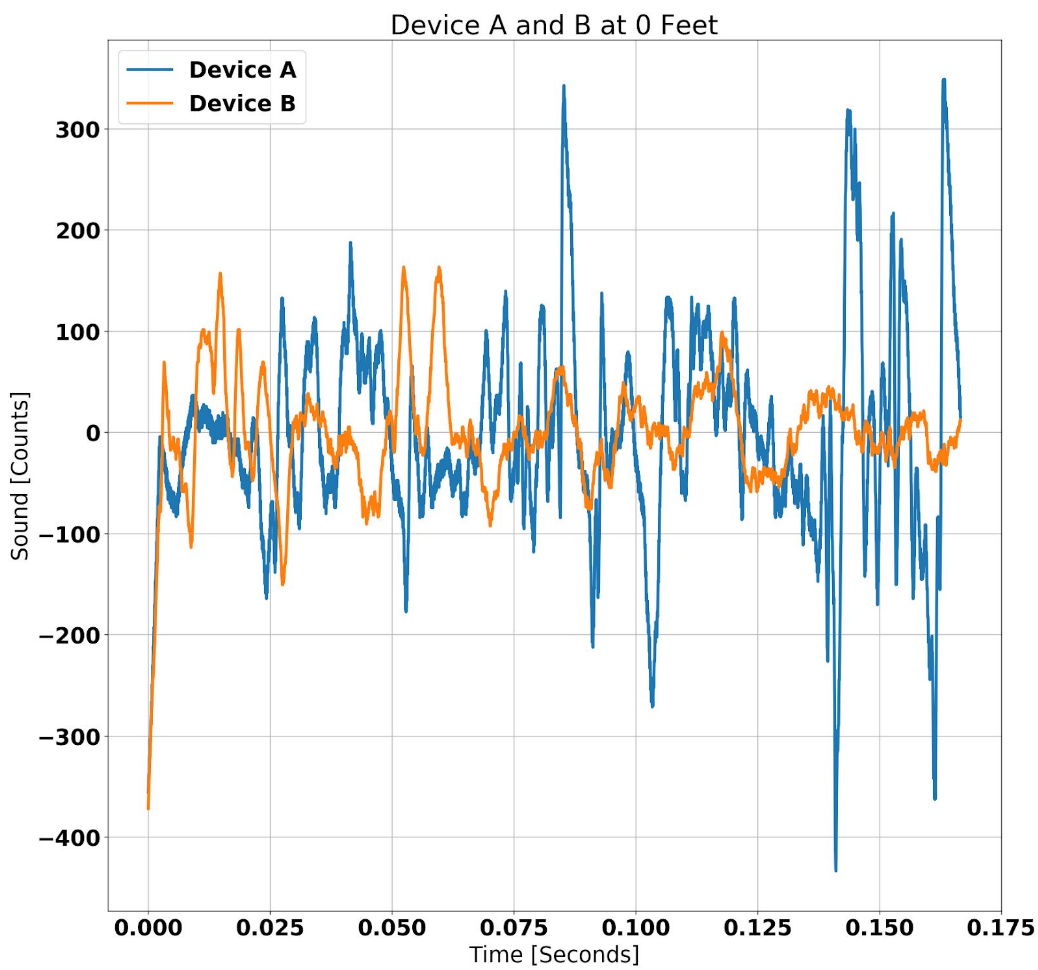


Figure 57: Sound at each distance from device C at 0 Hz to 500 Hz.

V. Overlaying raw sound

Our effort so far has been to detect the turbine by seeing some frequency range of sound. This approach was taken because we heard a sound of a specific frequency when taking data at the wind farm. The sound was quiet, but it was there and it was consistent. This led us to conclude that we would be able to detect the frequency of this sound and based our research on this assumption.

The wind turbine could be making sound in an inconsistent manner, resembling the wind. This would align with our result of detecting a lot of wind type sound and not disprove wind turbine noise. But a different method for confirming that the sound is coming from the wind turbine would need to be used. One method for detecting this type of sound is to look at the raw counts vs. time graph of two devices at different distances. Comparing the graphs, you would see if a set time after the first device detects a sound, the second device also detects a similar sound. If this set time is the distance from the two devices multiplied by the speed of sound, then it would indicate that the same sound passed through both devices. To confirm the sound was made by the wind turbine and not by wind, the counts would decrease with the devices farther from the wind turbine. We did not use any accurate timing device in our measurements and the task of aligning the timing of the devices based on the sound would be insufficient. We would align the time by looking at the sound and then make conclusions on the sound based on the timing. Due to wind, the sound profiles of each recording is very different from the next. We took simultaneous data for device A and B for the 0 feet location, the graph of the overlaid data is shown below:



The two devices started recording at the same time, within some human clicking error, at the same location. The graph shows a 1/6th of a second. Due to the amount of wind, fixing the human mistimed-clicking error to align the timing of the plots is non-trivial. Thus, a precise timing device would be necessary to use the above mentioned method. Zooming out from 1/6th of a second x-axis would not help, as it would lose information. The loss of information would be through the averaging of bins within pixels.

VI. Conclusion

The lack of detection of a wind turbine is likely due to several factors. One factor is that the wind was very heavy during the time when the data was taken. Wind turbine noise occurs at a very similar frequency to wind so any sounds from the turbine were not noticeable because the wind was much louder than the wind turbine. The data was also taken from the downwind side (facing away from the blades) of the wind turbine. Wind turbine noise has been shown to be louder on the upwind side than on the downwind side (Bolin 2011). This means there may have not been enough sound to be detectable at the locations where the measurements were taken.

Looking at the data in several different ways confirmed that LFN from a wind turbine was not differentiable from LFN from the wind. No trends were found in the frequency vs sound count graphs, the distance vs sound count graphs, or in the spectrograms. Despite being unable to detect wind turbine sound, we gained a lot of information about sound measurements that will be useful for similar studies in the future.

The absence of detectable wind turbine sounds may also be an indication that LFN near wind farms is not a large concern. Even within a few hundred feet of the turbine, the wind was significantly louder than the wind turbine. It is unlikely that people living near this wind farm would experience annoyance from the sound of the turbines.

Household Fan

We did not find any trends in the data taken from the wind turbine, but it is still possible to find results using our methods. We carried out a small-scale experiment under controlled conditions. The reason for carrying out this experiment was to collect data and analyze it the same way we analyzed our original data. We plotted the same graphs, looked for results, and tried to learn something new that could help us analyze our original wind turbine data. We conducted this small scale experiment for sound data only.

This experiment was done in a small sized bedroom with a household standing fan. The fan had three blades, and was 37 inches tall. Ten data points were recorded for this experiment. The first recording was in a silent room with the fan turned off and no air flow. The other nine recordings were carried out at three different distances from the base of the fan. The different distances were 0 inches, 40 inches, and 80 inches. Each distance had three recordings corresponding to three different speeds at which the fan was spinning. The device was placed in front of the fan. There were no vibrations from the fan and the only noise that was in the room was from the fan.

The data analysis process for the wind turbine data was also applied to the fan data. We ran a Fast Fourier Transform on the data and got distinct frequencies showing up on the graph. For the silent room data, the highest peak was at 125 Hz, and decreasing peaks in harmonics of 125 Hz until 750 Hz, then had a blank region until 1000 Hz (figure 58). At 1000 Hz, there was a peak that was the same size as the peak at 325 Hz. From 1000 Hz to 2000 Hz, the peaks are in the harmonics of 125 Hz again, but this time the peaks were smaller compared to the original peaks.

Peaks at 1000 Hz and 2000 Hz appeared in the fan data, the silent room data, and the wind turbine data. The intensity of these peaks is not constant, fluctuating between 75,000 counts to 150,000 counts in the household fan data. This tells us that it might be a property of the PCB or the FFT function. This data gave us a strong reasoning to ignore the 1000 Hz harmonic peak in our original wind turbine data.

The other thing we learned is that the spectrograms gave us reliable information about the wind turbine data. When we initially plotted the spectrogram for our wind turbine data, the plot was blurry and hard to read. We were not able to see any specific trends, so spectrograms were not much of a help. However, when we looked at the spectrograms of our household fan data, we were able to see the trends easily and the spectrograms agreed with the rest of the frequency graphs. This means that the reason why we couldn't see any trends in our data was because there was no visible trend.

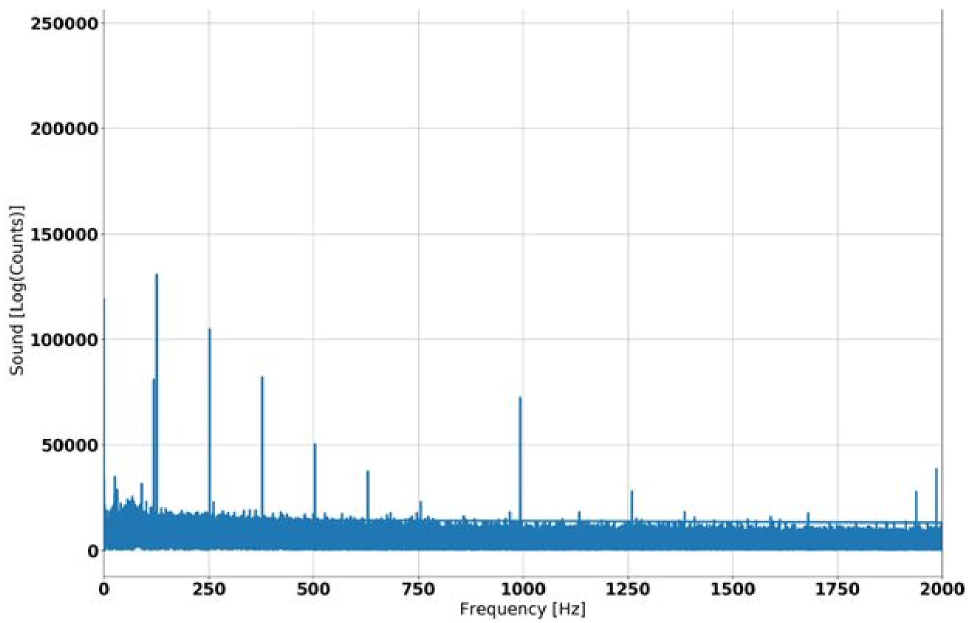


Figure 58: FFT graph of the silent room without a fan.

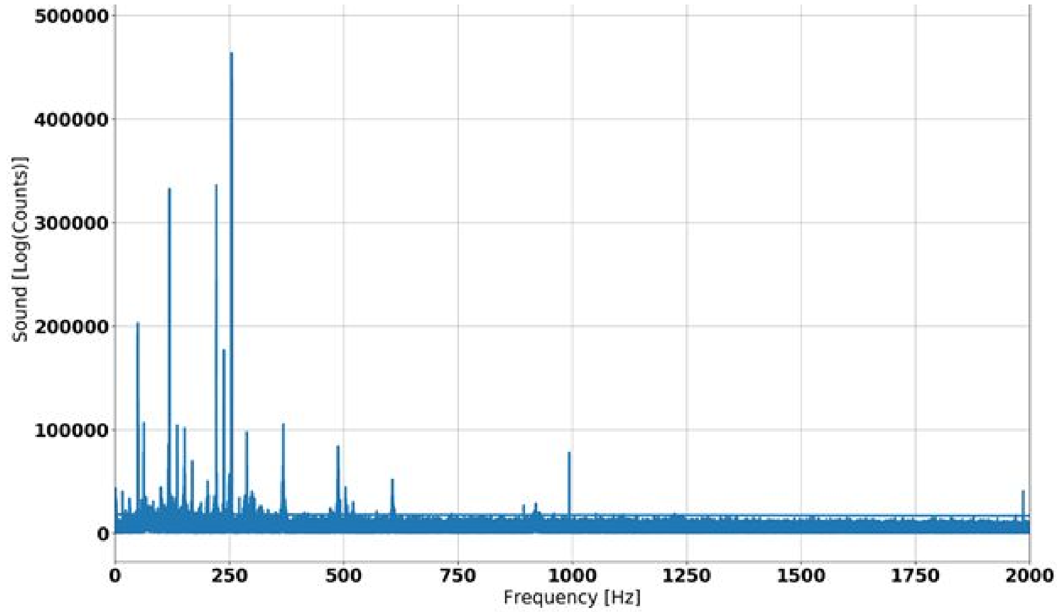


Figure 59: FFT of the recording at 0 inches from the fan at medium speed.

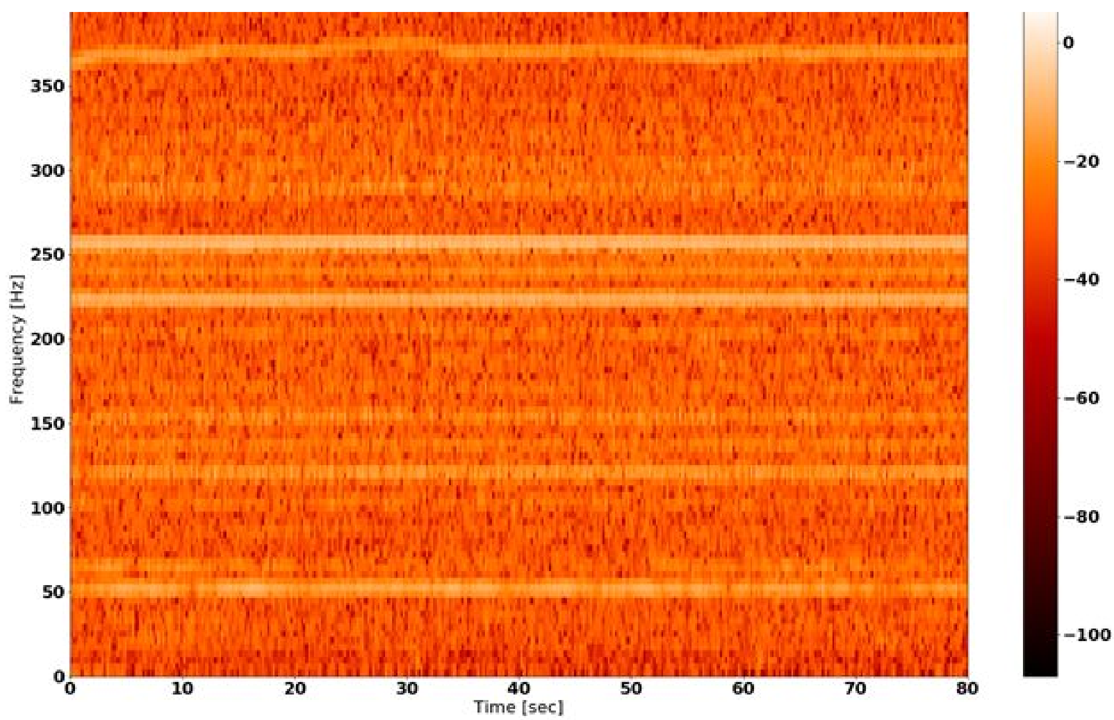


Figure 60: Spectrogram of the recording at 0 inches from the fan at medium speed.

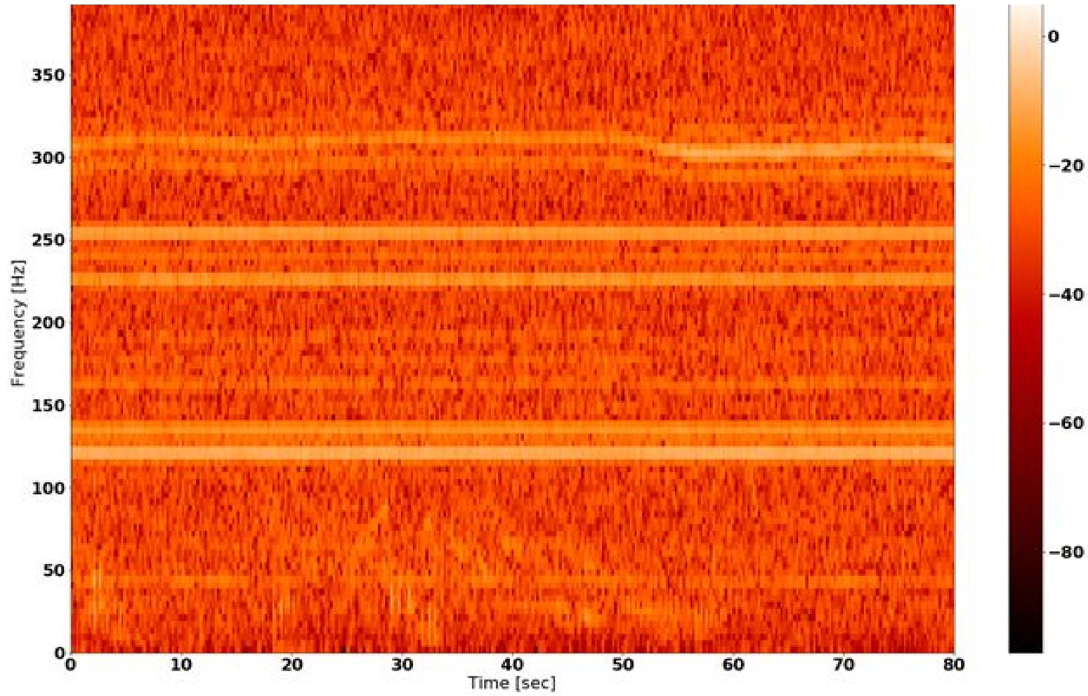


Figure 61: Spectrogram of the recording at 0 inches from the fan at low speed.

We used the household fan data to understand the spectrogram & FFT and how it would look when we produced the correct results. We learned which tools were useful and which weren't.

Improvements for Future Research

Now that we have a framework of what to do, there are some things that we would like to keep in mind if we ever collect wind turbine data again. This advice may be useful for future groups that decide to study this topic.

With regards to the data collection, we would have liked to be able to make measurements upwind and downwind from the wind turbine, to see if there are differences in the intensity of the sound measured. It also would have been ideal to gather data when it was less windy. Taking data sometime in the early morning or on a day that was less windy would result in less noise from wind and make it easier to detect noise from the turbine. This may be irrelevant for practical applications because high levels of wind are typical conditions for a wind farm, but would provide more information on the frequency of the sound. Due to unforeseen circumstances, the calibration of our devices was something we did not keep in mind. We were separated when we were preparing to record data, so calibration of the devices was not possible. Ideally we would have adjusted the microphone gains so that the ADC count from all devices was the same.

It is also possible that some parts of the devices were affected by the wind. The breadboard had many wires so it is possible that the wires shifted during recording, affecting the sound coming into the microphone. Securing the devices to the tables and taping down wires may reduce the error in the data. The last thing we learned is that the sound data was the most important and informative part of the data. We spent a lot of time making sure the BME 680, GPS, and anemometer worked, and did not have as much time to focus on the microphone and its functionalities.

As seen from the fan experiment, it is possible to detect sound from a rotating airfoil using our analysis method. But because of the amount of wind present on a wind farm, it is an impractical method for detecting the sound from a wind turbine. We recommend for future experiments that a different approach is taken. Using a real time clock to synchronize the devices, multiple distances from the wind turbine should be recorded exactly simultaneously. The pure sound count data can be analyzed to look for spikes that could indicate a sound from the wind turbine. This sound should occur at the further device slightly later in time at the closer device, and should have a smaller intensity. The time between when the sound occurs at the closer device and when it occurs at the further device should be approximately equal to the amount of time it takes for sound to travel between the two distances. An experiment such as this would be able to detect sound from the wind turbine and measure how fast the sound dissipates, but may not be as successful in determining the frequency of the sound.

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