



Bachelor's thesis

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***Characterization of Acoustic Sensors for the Pacific Ocean
Neutrino Experiment***

Abstract

P-ONE is an initiative to build a cubic-kilometer neutrino telescope located in the Pacific Ocean. This neutrino detector uses optical detection modules to detect Cherenkov light of neutrino interactions, thus making its geometry an important calibration parameter. This thesis aims to characterize the acoustic receivers used in the first P-ONE string based on the data recorded during the final acceptance test in the laboratory. The analysis of the acoustic data was conducted in two ways: time- and frequency-based analysis of signal properties. Therefore, the offset, standard deviation, peak-to-peak amplitude and root mean square of the output signal of the acoustic receivers have been chosen as time-based properties to characterize the signal in general. The scalings of these properties with pre-amplifier gain of acoustic receiver electronics and input frequency over all receivers are found to be in-line with design expectations, only for the signals offsets some deviation from the zero expectation are found at higher pre-amplifier gains. In addition, the frequency response of the receivers was examined using the signals' power spectrum. It was found, that receivers are able to resolve input frequencies in the target range of 10-60kHz with deviations less than or around 0.5Hz. The amplitude of the power spectrum was characterized, too. Here, we find the expected scaling with pre-amplifier gain but also dependence on the center frequency. Data of 41 acoustic receivers were analyzed in both time and frequency. Summary shows good agreement between devices. However, three receivers showed limited or invalid waveform data and are considered to have failed the test.

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1 Introduction

For modern astroparticle physics, neutrinos are one of the most important carriers of information about cosmic rays and their origin, especially on high energy scales [1]. Unlike gamma-ray observations, which are largely confined to our galaxy for energies above 100 TeV [2] since high-energy gamma rays are absorbed over intergalactic distances [1], neutrinos serve as ideal messengers, for example regarding particle interactions above the PeV scale [2]. This is primarily due to the fact that neutrinos interact only through the weak interaction and have a small cross section [1].

To get full sky neutrino coverage at the highest energies a global effort has been mobilized, containing several neutrino telescopes, such as KM3NeT and IceCube, as well as a new initiative to construct a multi-cubic kilometer neutrino telescope: the Pacific Ocean Neutrino Experiment (P-ONE) [2].

P-ONE is a new Cherenkov telescope optimized for TeV-PeV neutrinos, being built in the Pacific at a depth of 2660 meters, consisting of several strings carrying the detection modules [2]. As the ocean current will move those strings over time, which results in an error when reconstructing the neutrinos, constant position tracking of the modules is essential. This is done using acoustic systems. For this instance, each module contains two piezo-acoustic receivers, which can be used to determine the position of the modules at all times, with the help of acoustic beacons on the seafloor [3].

Before the first string of P-ONE (P-ONE-1), containing 20 modules, can be utilized, a final acceptance test was performed, using the Module Integration and Network Test (MINT) system, during which the acoustic receivers were tested [4].

The goal of this thesis is to characterize the acoustic receivers of P-ONE-1 using the test data of MINT by analyzing time-based properties as well as frequency-based properties of the signals. The general characterization takes place in the time domain, analyzing the offset, standard deviation, peak-to-peak amplitude and root mean square of the output signal of every acoustic receiver. In the frequency domain, the peak frequency of the power spectrum of the signal provides information about the frequency response of the acoustic receivers. Ultimately, the amplitude of this peak was also characterized for all receivers.

In section 2 of this thesis, an introduction in the physical concepts of neutrino physics, the P-ONE detector and the positioning tracking of the acoustic systems is given. In section 3, I describe the MINT system and present the mathematical methods that were used to define and gain all characterization properties. In section 4, first the time-based properties and second the frequency-based properties of all tested acoustic receivers were extracted, analyzed and compared. Finally, the characterization process gets summarized in section 5 and the most important findings are highlighted.

2 Scientific background

The Pacific Ocean Neutrino Experiment is an endeavor to build a neutrino detector in the Pacific Ocean [2], with the primary goal of detecting high-energy neutrinos. To understand the purpose of this detector and how it works, it is necessary to understand the physics behind neutrinos first.

2.1 Neutrino astronomy

Neutrinos are elementary particles with very small masses and no electric charge. They belong to the lepton family and currently three flavors are known: electron neutrinos ν_e , muon neutrinos ν_μ and tau neutrinos ν_τ , with each flavor corresponding to the respective charged lepton.

Since they carry no electric charge, neutrinos can only interact through weak interaction or gravity. But, as they have very low masses [5], gravity is usually not relevant for neutrino interactions. That leaves just the weak force for neutrinos to interact. This interaction has the smallest relative strength of interaction and neutrinos have small cross section [6]. This makes neutrinos the perfect source of information about the universe, because they are unlikely to interact with anything on their way from their source to earth, which gives us new insights for example about particle interaction above the PeV scale or high energy neutrino sources [2].

Understanding neutrinos above the PeV scale and from all directions, extremely large telescopes are needed to compensate the intrinsically small neutrino cross sections and the small neutrino flux at high energies [2]. The earth is transparent to neutrinos of energies higher than 50TeV [2]. So, to get information about neutrinos even at the highest energies, several telescopes are operating or in construction, among them P-ONE [2].

The Pacific Ocean Neutrino Experiment is an under-construction experiment in the Pacific Ocean. The primary target of P-ONE are muons of high energy (above 10TeV) [2], because of their long average propagation length through water. Those muons, produced through the interaction of a high-energy neutrino, can be detected via Cherenkov light [2]. If a muon travels through a medium with refractive index n it polarizes the molecules in the medium. Generally, the polarized particles return to their unpolarized states by emitting photons [7]. The phase shift of the emitted light waves depends on the ratio of the muon's particle velocity to the medium's phase velocity $\frac{v}{c_m}$, with the phase velocity $c_m = \frac{c}{n}$. If the muon's velocity is greater than this phase velocity, partial waves can interfere constructively [8].

This leads to the emission of Cherenkov light as a coherent wavefront, which can be seen in Figure 1. The wavefront gets emitted at a fixed angle to the trajectory of the charged particle, which can be calculated with

$$\cos \theta = \frac{1}{n\beta} \quad (1)$$

and $\beta = \frac{v}{c}$ [7]. P-ONE will detect this Cherenkov light, which in theory allows the reconstruction of the incoming neutrinos with an angular resolution of a fraction of a degree [2]. This Cherenkov light can be detected via the photomultiplier tubes (PMTs) of the P-ONE detector.

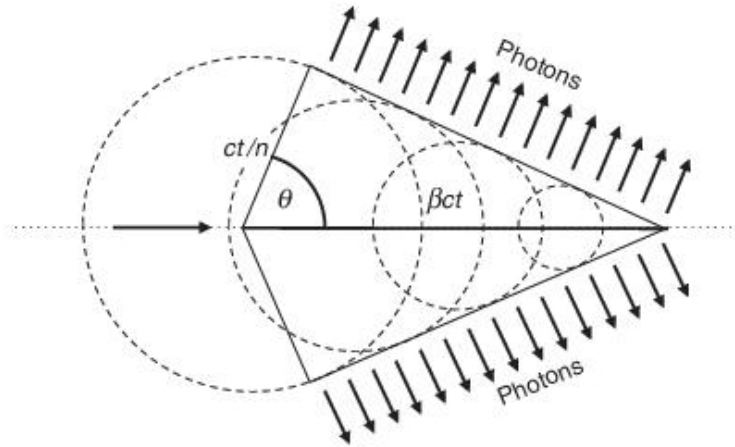


Figure 1: Geometry of the emission of Cherenkov radiation. Figure taken from [7].

2.2 The P-ONE detector

The P-ONE detector is a neutrino detector, optimized for energies of 10TeV-10PeV [2]. It will be constructed in the Pacific Ocean at Cascadia Basin, located off the coast of Vancouver Island, Canada, in a depth of around 2600m [9]. This location brings a few advantages, such as a temperature of below 2°C [2], but mostly an already existing robust undersea infrastructure, that can be used for installation of the detector. This infrastructure is called NEPTUNE and is hosted by Ocean Networks Canada (ONC), which provides existing expertise and knowledge about deployment, operation, and maintenance of complex deep-sea equipment [10].

It is planned that the detector will consist of seven clusters each containing 10 instrumented mooring lines. Each string will be 1000m long and will contain the modules for the measurements [9].

There are two types of modules: the P-ONE Optical Modules (P-OM), which will be measurement units, and the Calibration Modules (P-CAL) [10]. All modules are encapsulated in 17-inch glass spheres and are containing PMTs for the detection of Cherenkov light [9]. Each module has two hemispheres. 16 PMTs (Hamamatsu R14374-10) are installed in each P-OM, 8 in each hemisphere. In P-CALs, 4 PMTs in each hemisphere are replaced with a diffuse flasher system [11].

P-ONE-1, the first P-ONE string, will contain 18 P-OMs and 2 P-CALs [11], which will all be carried by a backbone cable [10]. This cable terminates in a string junction box (sJB) [12], which will serve as the interfacing point to the NEPTUNE network [10].

Figure 2 shows the two module types and in Figure 3 the detector design and a cluster of the detector can be seen. The distribution of PMTs, OMs and strings in the detector allows the reconstruction of neutrinos. But the strings are moved by water current and are changing position over time. For this reason, it is extremely important to track the movement of the detector geometry, so there are smaller errors in the location of the modules and therefore a higher accuracy of the reconstruction [13]. For this purpose, the acoustic system will be used for continuous positioning for the detector modules [3].

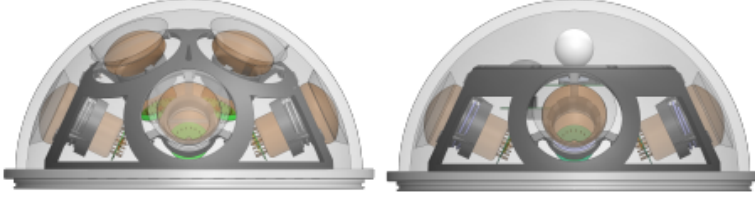


Figure 2: Layout of a P-OM (left) and a P-CAL (right). Image taken from [9].

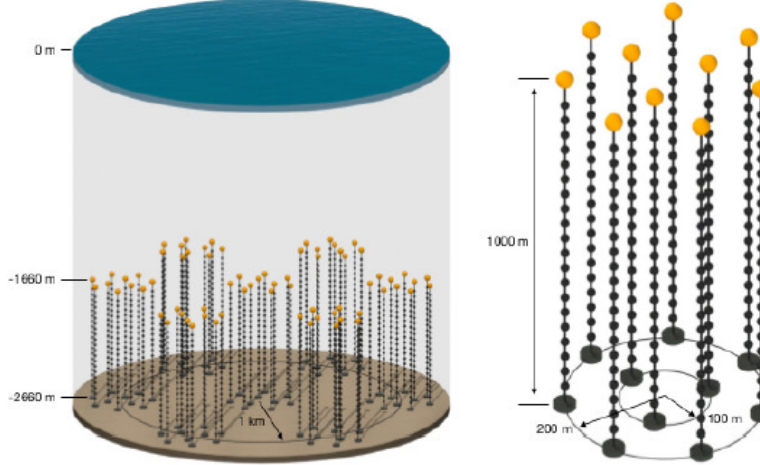
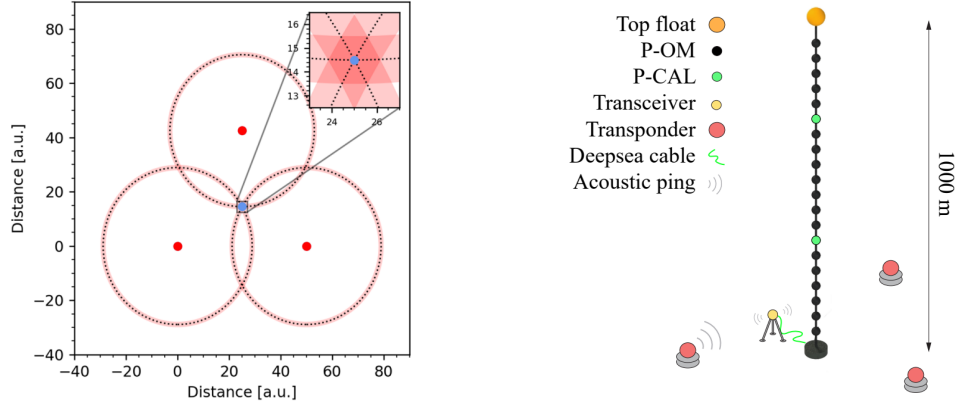


Figure 3: Detector layout of P-ONE (left) and a single cluster (right). Image taken from [9].

2.3 Acoustic Systems in P-ONE

The acoustic systems in P-ONE are responsible for precisely determining the position of each module at all times. As already mentioned, a constant calibration of the positions of the modules leads to better reconstruction of the neutrinos. The PMTs in P-ONE have an approximate resolution of 1ns. This requires a relative positioning resolution of significantly better 20cm [3].

To achieve this goal, multilateration of acoustic signals is used. Figure 4a shows multilateration as an example with three beacons (trilateration) in two dimensions. You can see that the three beacons at known positions send out signals and, when they get to the point of interest, the time, that the three signals needed to travel through the medium to the point of interest, is measured [13]. With knowledge of the speed of sound and the propagation of acoustic signals in water these time of flights (TOFs) can be converted to ranges from a beacon to the point of interest and using all three ranges, the position of the point of interest can be found [3]. For multilateration, more beacons are used to reduce systematic uncertainties [13]. Using multilateration in three dimensions and acoustic receivers in every module, the position of every module can constantly be tracked. It is planned to use multiple acoustic beacons within the instrumented volume of P-ONE. Figure 4b shows the layout that can be used for multilateration with three beacons at one string. The transceiver is used for acoustically communication with the



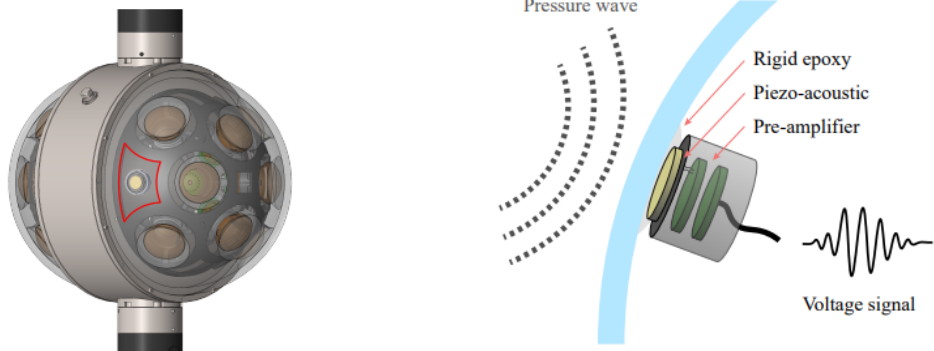
(a) Two dimensional trilateration of a point of interest (blue) with the help of three beacons (red). The width of the waveforms represent the error in timing.

(b) P-ONE acoustic calibration seafloor system, containing the P-OMs and P-CALs, with acoustic receivers included, an acoustic transceiver and the beacons.

Figure 4: Multilateration concept in two dimensions (left, image taken from [13]) and as used on a P-ONE string (right, image taken from [3]).

beacons and to control them [3]. The beacons position can be found with high precision using GPS-based surface positioning methods, e. g. [14]. So the position of the modules is primarily determined by how accurately the acoustic signals propagating between beacons and piezo-acoustic receivers and their true TOF can be reconstructed [3]. To track the positions of all of these modules, every module will have two piezo-acoustic receivers, one in every hemisphere of the module, integrated inside the instrument's glass pressure housing, which is shown in Figure 5a.

For this reason, acoustic signals have to be picked up via the glass pressure housing. The pressure housing acts as a resonator and transmits external acoustic pressure waves. This is why the acoustic signal is expected to be damped. The detection concept is modulated in Figure 5b.



(a) Piezo-acoustic receiver (yellow) integrated in a P-OM.

(b) Detection concept of the piezo-acoustic receiver.

Figure 5: Integration and concept of the piezo-acoustic receiver in an P-OM. Both images taken from [3].

After the housing transmitted the acoustic waves, the piezo-acoustic disk, glued to the glass, responds to the transmitted vibration with voltage signals. A pre-amplifier amplifies the small voltage signal after a 5-stage active high-pass filter with a roll-off frequency at 10kHz removed low-frequency noise. The gain of both stages on the amplifier can have values from 0 to 64, configurable through a serial peripheral interface. The resulting signal can then be digitized and used for further processing [3].

The piezo-acoustic element used is PIC255 from PI Ceramic with a wrapped-electrode configuration [3]. It has an outer diameter of 16 mm and a thickness of 2 mm and it exhibits longitudinal resonance frequencies of 1MHz and radial resonance frequencies of 125kHz, which are far outside of the used frequency band. The receivers housing consists of aluminum, providing a lightweight shield against electromagnetic interference expected from the electronics of the P-OM [3].

The digitization is done with an analog-to-digital converter (ADC, TLV320ADC6140 by Texas Instruments). It will be operated in differential input mode and with a sampling rate of 192kHz, which is sufficient for the signals of interest, which includes frequencies between 19-50kHz [3, 4].

For further information about the mechanical layout and the installation of the receiver, as well as filtering, amplification and digitization of the signal coming from the piezo-acoustic element, refer to [3].

3 Methods

3.1 Module Integration and Network Testing (MINT)

P-ONE-1 is the first string of P-ONE, consisting of 18 P-OMs and 2 P-CALs. The Module Integration and Network Test (MINT) system is the final acceptance test system for this first string. The goal of it was to verify that all subsystems in the modules were functional and that they meet their acceptance criteria [4].

Although this system tested several components of each P-ONE-1 module, the acoustic tests are the focus of this thesis. My goal was to characterize the MINT data taken for all acoustic receivers in P-ONE-1. Tested variables were frequency response, gain and signal properties. In the MINT, piezo buzzers were mounted on the outside of the glass hemisphere, sending signals generated by a function generator [4]. A sketch of the test setup can be seen in Figure 6. Then, for each of the modules the buzzer send out a signal

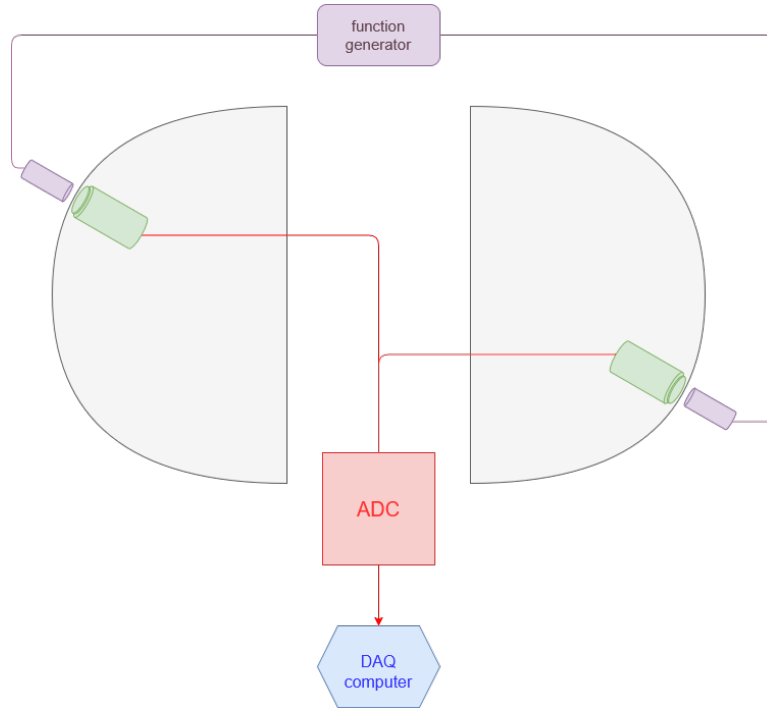


Figure 6: Sketch of MINT system test setup for acoustic receivers (green) with external function generator, creating the input signals for the buzzers (purple) mounted on the glass of the hemispheres (gray). Measured signals of both receivers in a module get digitized through a singular ADC (red). Ultimately, the digitized signal ends at the control computer (blue).

with a frequency of 10kHz, 20kHz, 30kHz, 40kHz, 50kHz or 60kHz and the gain settings were set to 1-1, 2-2, 4-4, 8-8, 16-16 or 32-32. Each of this combinations was measured once for each receiver, so 36 measurements per module, and both receivers of a module were measured at the same time. The signals of the piezo-acoustic elements of both receivers were digitized simultaneously by the ADC, giving two ADC channels, each describing one receiver. In addition to this 36 measurements per module, background measurements were taken for every module and gain setting, where the buzzer send no

signal, giving us the system background for every gain setting of every receiver [4]. A total of 41 hemispheres were tested in the MINT, of which 40 were ultimately installed for P-ONE-1 [4]. And for each receiver, 42 measurements were taken with each giving one signal back from the piezo-acoustic element. With this data, the characterization of the acoustic elements of P-ONE-1 can be performed. This characterization is relative between receivers, which means the source spectrum of the source buzzer is not corrected for.

3.2 Time-based analysis

The constant sinusoidal signal coupled into the receiver system is, to first order, expected to produce a matching sinusoidal response. To understand the techniques used in analyzing these data, we walk through all analysis steps using an artificial sinusoidal signal as shown in Figure 7. In this plot an ideal sine with an frequency of 30 kHz can

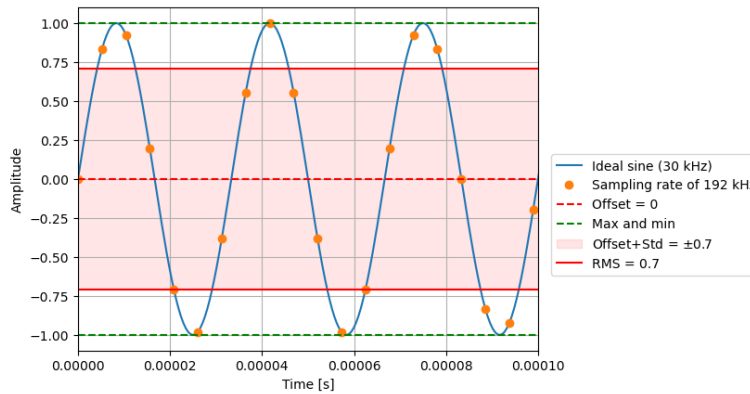


Figure 7: Artificial example of an output signal of the MINT-ADC. It resembles an ideal sine with a frequency of 30 kHz and the same sine with a sample rate of 192 kHz. The offset, the minimal and maximal value, the standard deviation and the root mean square of the sampled signal can also be seen. The duration time of the signal was 1.0003s

be seen in blue. The corresponding function is

$$x(t) = A \sin(2\pi ft) + c \quad (2)$$

where $f = 30$ kHz, A is the amplitude, in the example it is 1, and c the offset. With infinite time resolution and no other disturbing factors the receiver should produce an amplified version of this signal when giving a 30 kHz sine to the buzzer input. In reality however the P-ONE DAQ has a finite sampling rate of 192kHz and the electronics and mechanics of the receiver system will result in modification of the frequency response. However, for the artificial example a ideal sine with a sampling rate of 192kHz will be assumed for identifying performance metrics of the output signals.

In the time base, we can characterize general properties of the sinusoidal signal described by Equation 2. This includes offset, standard deviation, peak-to-peak amplitude and root mean square.

The first observable is the offset characterized as the mean value

$$\bar{x} = c = \frac{1}{N} \sum_{i=1}^N x_i \quad (3)$$

over all measurement points. In general, the signal could have a constant offset. However, due to the alternating-current (AC) coupling of the receiver electronics, we expect the offsets for all receivers to sit around $c = 0$. But due to systematic effect as for example the finite sampling or effects of the receiver electronics, offsets different from 0 are possible and therefore will be characterized explicitly.

To this offset the standard deviation of the signal, related to the spread of sampling points in data as shown by the red-shaded area in Figure 7, can be calculated.

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})^2} \quad (4)$$

In addition you can calculate the peak-to-peak amplitude of the measurement points in Figure 7 by determining the maximum and minimum values and then subtracting one from the other.

$$\Delta x_{\text{ptp}} = x_{\text{max}} - x_{\text{min}} \quad (5)$$

This makes it easy to check whether the signals from different receivers are of the same order of magnitude or whether they differ directly in their amplitude.

The last observable we characterize in the time base is the root mean square (RMS).

$$x_{\text{RMS}} = \sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2} \quad (6)$$

This describes the effective magnitude of the signal by indicating the deviation from 0. In the example of Figure 7 the RMS is equal to the standard deviation because $c = 0$. These observables can be used to perform an initial characterization of the raw signal and compare the analog output signals in the time domain.

3.3 Frequency-based analysis

A more comprehensive analysis is performed in the frequency domain. To accomplish this, a periodogram was generated for each raw signal and the peak frequency was then determined using a Lorentzian fit. This peak frequency, along with its error margin from the fit, indicates how well the receivers can resolve incoming frequencies.

To obtain the frequency response of every receiver you can use a spectrogram or a periodogram. In the analysis, both techniques were tested and the final evaluation was done with a periodogram because spectrograms artificially reduce frequency resolution. The definition of a periodogram is illustrated using again the example from Figure 7. Assuming the receivers signal is sinusoidal, let's call it $x[n]$ which gives the measurement point in n th position. The parameter $n \in \mathbb{N}$ is in an interval of $0 \leq n \leq N - 1$ and N ,

the number of measurement points is set by multiplying the sampling rate with the duration time of the signal.

$$N = f_s \cdot t \quad (7)$$

The periodogram is then derived by first applying the Fast Fourier Transform (FFT) to it

$$X[k] = \sum_{n=0}^{N_{\text{FFT}}-1} x[n] \exp\left(\frac{-2\pi i k n}{N_{\text{FFT}}}\right) \quad (8)$$

where k are the Fourier coefficients proportional to the signal power at certain frequencies and N_{FFT} the length of the FFT, equal to N by default. After that the absolute value of the transformed signal is calculated, which is then squared and normalized by the number of measurement points squared.

$$P[k] = \frac{|X[k]|^2}{N^2} \quad (9)$$

The result is the squared signal amplitude per FFT bin. The frequency axis is calculated as frequency values as a function of the FFT bin k using the equation

$$f[k] = k \frac{f_s}{N_{\text{FFT}}} \quad (10)$$

where f_s equals the sampling rate of 192kHz.

In case you want to subtract periodograms from each other, they need to match in size. This is done when subtracting the background periodograms from the periodograms with a test signal in the analysis. For this purpose you must set the N_{FFT} parameter equal for both periodograms. Therefore, there are two possible ways to achieve this: you can use the smaller N of both traces as N_{FFT} for both periodograms or 0-pad the shorter trace. For $N_{\text{FFT}} > N$, this means, that in the FFT of the signal no new terms get added, but the FFT gains more frequency bins for the same spectral information, because the bin width

$$\Delta f = \frac{f_s}{N_{\text{FFT}}} \quad (11)$$

gets smaller. It is the same information but sampled more finely. This happens by using N of the signal with more measurement points as N_{FFT} for both FFTs. The periodogram of the signal with less measurement points will have more spectral information, because it has $N_{\text{FFT}} > N$ and therefore gets sampled more finely.

An alternative is to set $N_{\text{FFT}} < N$ for the signal with more measurement points, which leads to cutting out the excess data points of the signal for the FFT. Then, this periodogram loses spectral information, but both have the same amount of spectral information to compare.

The resulting periodogram is then converted to dB units using the equation

$$P_{dB} = 10 \cdot \log_{10}(P[k]) \quad (12)$$

The result is the power spectrum shown in Figure 8. Windowing functions (e.g. boxcar, or hann) can be applied to the FFT, effectively multiplying the signal as

$$x_s = x[n] \cdot x_w \quad (13)$$

before the FFT gets applied, see [15] and references therein. For boxcar the factor is just 1. For hann the window is defined as [16]

$$x_w = 0.5 - 0.5 \cos\left(\frac{2\pi n}{N-1}\right) \quad 0 \leq n \leq N-1 \quad (14)$$

In the frequency domain, Equation 13 yields a convolution of the spectra

$$X[k]_{\text{FFT}} = X[k] * W \quad (15)$$

where W is the spectrum of x_w . The boxcar window leaves the signal unmodified. The FFT for x_w is, in this case, a sinc-function. This leads to a narrow main lobe and many side lobes. If the signal frequency lies perfectly at one FFT bin, you get just one narrow peak, as is demonstrated by the blue graph of the ideal sine in Figure 8. If this is not the case, as is artificially shown by the orange curve with $N = f_s \cdot t = 192057.6$, so that the samples get rounded off to 192057, we get a bin width of $\Delta f = \frac{192000}{192057} \approx 0.9997$ and an exact FFT bin of $k = \frac{30\text{kHz}}{\Delta f} \approx 30009.003$, so the power spectrum of the frequency gets departed in more bins and it comes to leakage.

The hann window on the other hand causes the signal to be greatly amplified in the middle and to decrease at the edges. Its FFT is a combination of three overlaying sinc-functions. They add up in the middle and cancel each other out at the side lobes, which causes a wider peak in the middle but almost no side lobes. This is shown in the hann graphs off Figure 8, where the sampled graphs have leakage again.

In the following we consider both windowing options, the boxcar window for physical accuracy and the hann window for increased signal-to-noise ratio in the early analysis. The periodograms were done with the `scipy.signal` function 'periodogram' using both windows, which shows the same outcome as the power spectrum of the raw FFT as can be seen in Figure 8 when using the same windowing.

The red signal is an example for how a periodogram will look like with our data and hann window, if the data were ideal without any noise. The noise in MINT can be assumed to be white noise. This means, that the frequency characteristics of this noise stays constant over frequency. You can make this assumption, because the noise in the test comes from systematic sources such as the electronics used in the test and therefore should always have the same frequency characteristics. To resemble a noisy periodogram I converted the ideal sine into a sine with a random white noise

$$x_s = x[n] + x_{\text{noise}} \quad (16)$$

where x_{noise} is a gaussian distributed series of random numbers with a mean of 0 and a standard deviation of 0.2, as can be seen in Figure 9. When you plot the periodogram of this signal, you can see that smaller peaks also appear in other frequency bins, as in the brown graph of Figure 8. To characterize the frequency response of the receivers certain fits were used. A Lorentzian fit with constant background is one possible fit for

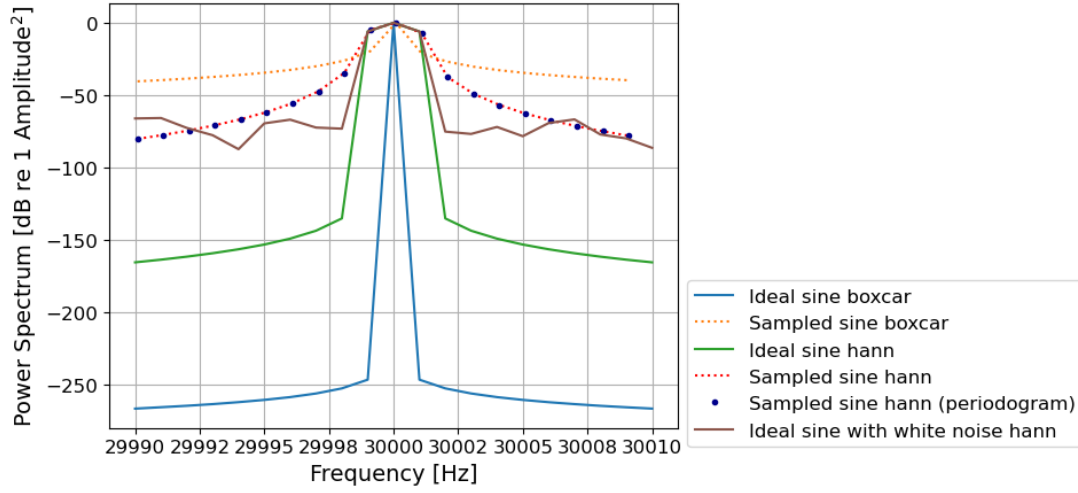


Figure 8: Power spectra of 30kHz sines. All graphs other than the dark blue one are performed with the raw FFT values and $N_{\text{FFT}} = N$. The dark blue power spectrum is a periodogram made with the `scipy.signal` function `periodogram` with a hann window, $N_{\text{FFT}} = N$ and `scaling = spectrum`. The sampling rates of the orange, dark blue and red graphs are 192kHz. The duration of the signal is 1.0003s.

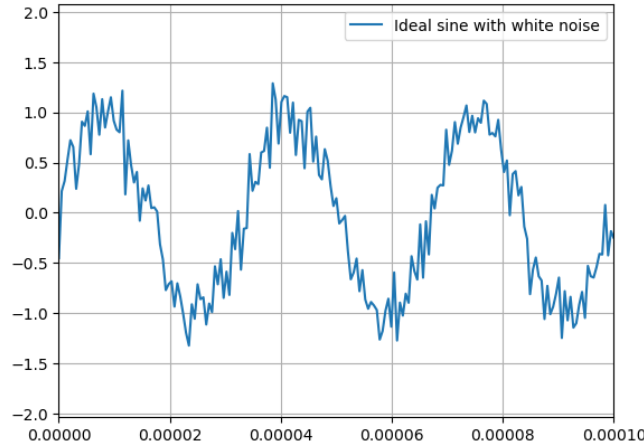


Figure 9: Ideal sine with 30kHz and random white noise.

this purpose. Consider that the receiver system can be, to first order, described as a damped harmonic oscillator. The signals function is then

$$x_s(t) = A \cdot \exp(-\gamma\omega t) \exp(i\omega_0 t) \quad (17)$$

with A being the signals amplitude, γ the damping coefficient and $\omega_0 = 2\pi f_0$. The FFT of this signal equals

$$X(\omega) = \frac{A}{\gamma\omega + i(\omega - \omega_0)} \quad (18)$$

and the squared magnitude of this FFT is given by

$$|X(\omega)|^2 = \frac{A^2}{1 + \left(\frac{\omega - \omega_0}{\gamma\omega}\right)^2} \quad (19)$$

and assuming a constant background you get a Lorentzian curve

$$L(f) = \frac{A_p}{1 + \left(\frac{f - f_0}{\gamma}\right)^2} + c \quad (20)$$

and the logarithmic Lorentzian fit after converting the curve to dB units

$$P(f) = 10 \cdot \log_{10} \left(\frac{A_p}{1 + \left(\frac{f - f_0}{\gamma}\right)^2} + c \right) \quad (21)$$

where $\gamma = \frac{\gamma\omega}{2\pi}$ and $A_p = A^2$. This fit closely reflects the peak shape in the periodogram and can therefore be used to determine the peak frequency, which is specified by the parameter f_0 . The parameter γ is an indicator for the width of the peak and therefore gives us a measure for how sharply the frequency can be resolved. The peak frequency thus indicates the frequency at which the power spectrum is highest, and therefore should correspond to the frequency of the sinusoidal signal measured by the receiver. This value can then be compared with the input frequency, allowing us to determine how well the receiver responds to a specific frequency at a specific gain.

The Parameter A_p resembles the squared amplitude of the Peak and therefore the respective amount of power which also can be compared between receivers to characterize relative sensitivity as a function of gain.

To perform the fits, `curve_fit` from the `scipy.optimize` package was used, using physical bounds on all fit parameters. This returns the optimal fit values for the parameters so that the sum of the squared residuals of

$$f(\text{xdata}, *popt) - \text{ydata} \quad (22)$$

is minimized, where `xdata` and `ydata` are the actual data points and `*popt` the optimal parameters of the fit [17].

In addition to the physically motivated Lorentzian fit, the analysis also uses a Gaussian fit with linear background of the shape

$$G(f) = A \cdot \exp\left(-\frac{(f - \mu)^2}{2 \cdot \sigma^2}\right) + m \cdot f + t \quad (23)$$

or double Gaussian fits with constant offset

$$G(f)_{double} = A_1 \cdot \exp\left(-\frac{(f - \mu_1)^2}{2 \cdot \sigma_1^2}\right) + A_2 \cdot \exp\left(-\frac{(f - \mu_2)^2}{2 \cdot \sigma_2^2}\right) + c \quad (24)$$

for periodograms with hann window. For these windows, the physically motivation of a fit of the form of Equation 21 is no longer given. Although, in the early stages of the analysis, hann windows were used for better signal-to-noise ratio and for this different shaped peaks, different fits were performed to look at which fit suits the data best.

For different stages in the analysis, depending on the type of fit used, the fit parameter bounds were adjusted accordingly. The frequency window used to determine in which range the frequency peak around the input frequency of the buzzer could be fitted, is listed for every analysis step in Appendix A.

To compare different fits with each other, the χ^2 value defined as

$$\chi^2 = \sum_i \frac{(P - P_{\text{fit}})^2}{|P|} \quad (25)$$

was used, where P resembles the actual power spectrum points and P_{fit} the fitted values. This was used as a way to check the overall deviation of the fit from the data using appropriate normalization.

It is possible to do the complete analysis with a spectrogram too. Simply put, a spectrogram consists of several periodograms and, in addition to power, also indicates the temporal variation in frequency power. To do this, the signal is divided into several small time segments. A separate periodogram is calculated for each of these segments. This is particularly useful if the frequencies change over time, although this is not the case for the data used in this thesis. For a constant signal, the periodogram is more suitable, as it reflects the entire signal without dividing it into subintervals. Furthermore, the frequency resolution in the spectrogram decreases with the size of the time window. In Figure 10 two spectrograms with hann windowing can be seen for the example 30kHz sine from Figure 7 with two different sizes of the segments. The plot with the larger N_{FFT} value, which is the number of data points used in each block for the FFT, has the larger time segments $\Delta t = \frac{N_{\text{FFT}}}{f_s}$ and therefore a better frequency resolution $\Delta f = \frac{f_s}{N_{\text{FFT}}}$. If you average the spectrogram now over time you would get a power spectrum which is

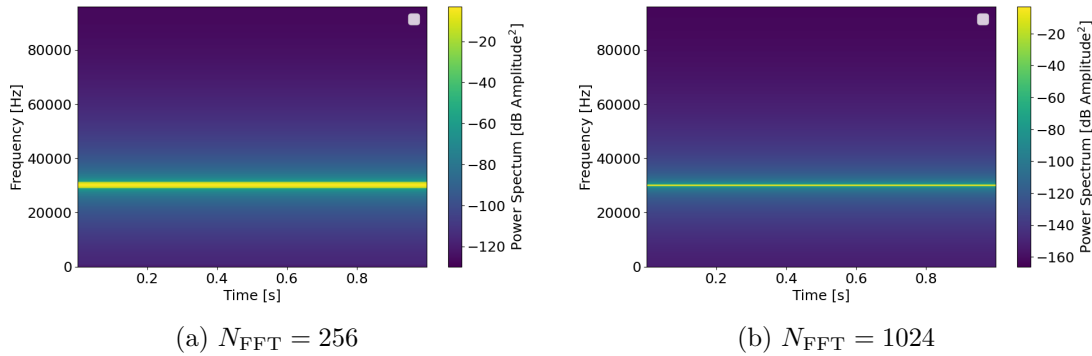


Figure 10: Spectrograms of the ideal sine signal with $f = 30\text{kHz}$ and $f_s = 192\text{kHz}$ for two different sizes of the segments.

equal to a periodogram and from this spectrum you can also find the peak frequency, but you just loose resolution by cutting the signal in segments and later averaging again over time. This can be seen in Figure 11, where the form of the averaged spectrogram looks like a periodogram with hann window, but the peak of the periodogram is quite more prominent and they differ in amplitude too. If you use an N_{FFT} value equal to the number of data points of the signal, you would even get the periodogram, but you lose time resolution completely, which is the only aspect, why the spectrogram would be more useful than the periodogram. But because there is no need for time resolution

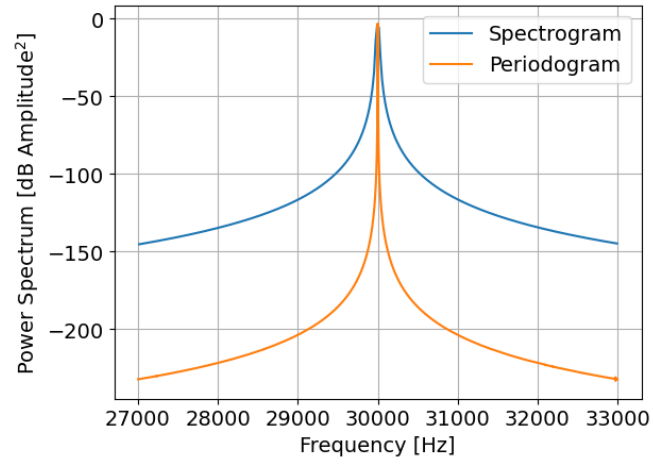


Figure 11: Power spectra of the ideal sine signal with 30kHz, performed with a spectrogram with $N_{\text{FFT}} = \frac{N}{20}$ (blue) as well as with a periodogram with $N_{\text{FFT}} = N$ (orange).

in the first place, because we have a constant frequency signal, the periodogram makes more sense to use for the frequency evaluation.

4 Results

4.1 Time-based receiver properties

One of the goals of my thesis was to determine whether there are systematic differences in the time-based signals measured by the receivers, and whether receivers behave differently at different gains and input frequencies. To do this, we first examine the raw output signal over time that a specific receiver with a specific gain setting receives at a specific input frequency. An example of such an output signal is shown in Figure 12. In this matter each channel equals one receiver in one of the hemispheres in

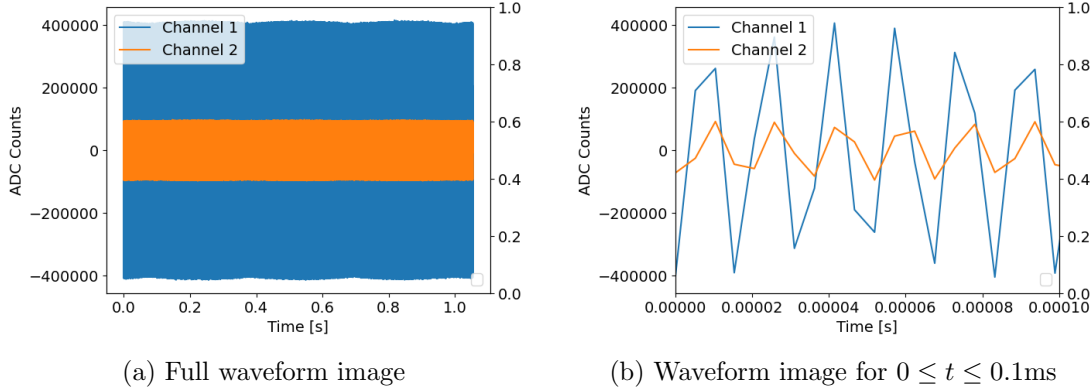


Figure 12: Waveform image for module 3620 for both channels with gain 8-8 and input frequency of 60kHz.

the module. For each module the ADC counts of both receivers were measured at 0kHz, 10kHz, 20kHz, 30kHz, 40kHz, 50kHz and 60kHz, as well as for the gains 1-1, 2-2, 4-4, 8-8, 16-16 and 32-32, in all possible combinations. The measurements with 0kHz were done as background measurements of the respective module with the same gain setting. Without these background measurements, for every module 36 separate measurements with variation in gain and input frequency were performed and for each of this measurements you can find the metrics to characterize the time-based properties described in subsection 3.2.

While performing the test some measurements did not contain valid data, the receiver did not measure any signal or the measured signal had no clear frequency peak. This measurements are listed in Table 1. For CAL-0305 receiver 1, there was an error

Receiver	Error
CAL-0305, ch1	no signal
OM-hs-11, ch2	ch1 only
OM-4035, ch2	small frequency peak
OM-4103, ch2	small frequency peak
OM-0204, ch1, gain 16-16, 60kHz	no data
OM-3810, ch1, gain 32-32, 60kHz	no data

Table 1: List of receivers with errors and their assumed reasons.

with the acoustic hemisphere. For OM-hs-11, the second channel is only the second ACD channel, but only one hemisphere was measured. So in both cases, there should be no signal. But there is actually a weak signal coming from those two ADC channels, which is probably a crosstalk signal from the other receiver. The signals of OM-4035 and OM-4103 are measurements with pretty small frequency peaks for many measurements, as the analysis will show.

Those measurements are included in the analysis and all plots, because they also had output signals, which need to be characterized, although the information of this measurements cannot be compared to the normal working test measurements. The inclusion of this measurements though sets a bigger uncertainty to all plots showing average values.

The only two measurements which are not included in any plots are the 60kHz measurements of OM-0204 channel 1 with gain 16-16 and OM-3810 channel 1 with gain 32-32, because the ADC traces no data.

4.1.1 Offset

The first time-based property you can look at is the offset of each signal when detected by the receiver. Because there was no initial offset given by the input signal, the amount of the offset of each measurement should be pretty small. To check this, you can plot the offset value over the input frequency of the receiver for each gain setting. In Figure 13, an example of this plots can be seen.

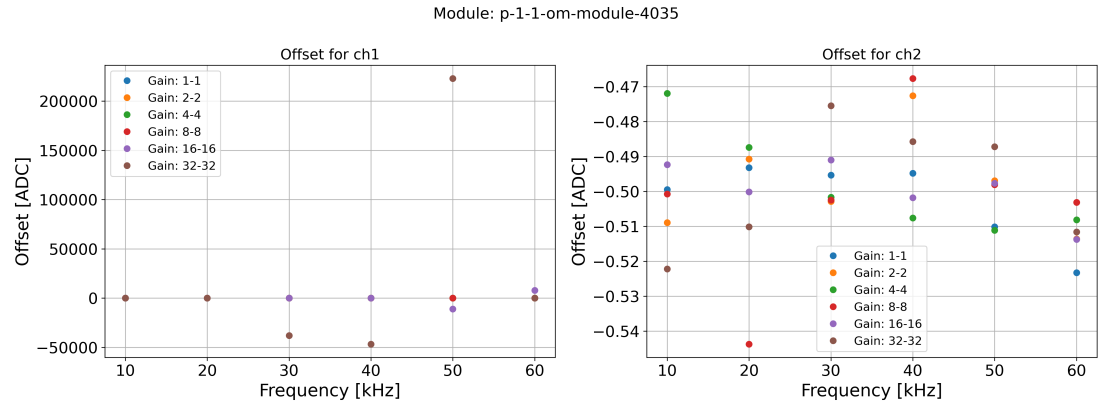


Figure 13: Plot of the offset value over the input frequency for all gain settings of both channels of OM-4035.

Channel 2 of OM-4035 shows the expected variation of the offset closely around 0. In channel 1 several points also lie around 0, although there are several points further away, especially the points for gain 32-32. This behavior can be observed in most of the other receivers, too. Their plots are included in Appendix B. To get a better view at how the offset is distributed between modules of the same gain for all frequencies, I also performed a plot showing 6 subfigures which each contain the offset of all modules for all frequencies for one specific gain setting. This plot is shown in Figure 14. You can see that for smaller gains the points are distributed closer around 0 with less points further away and with rising gain the distance between 0 and some offset points get greater and the number of those points is increasing.

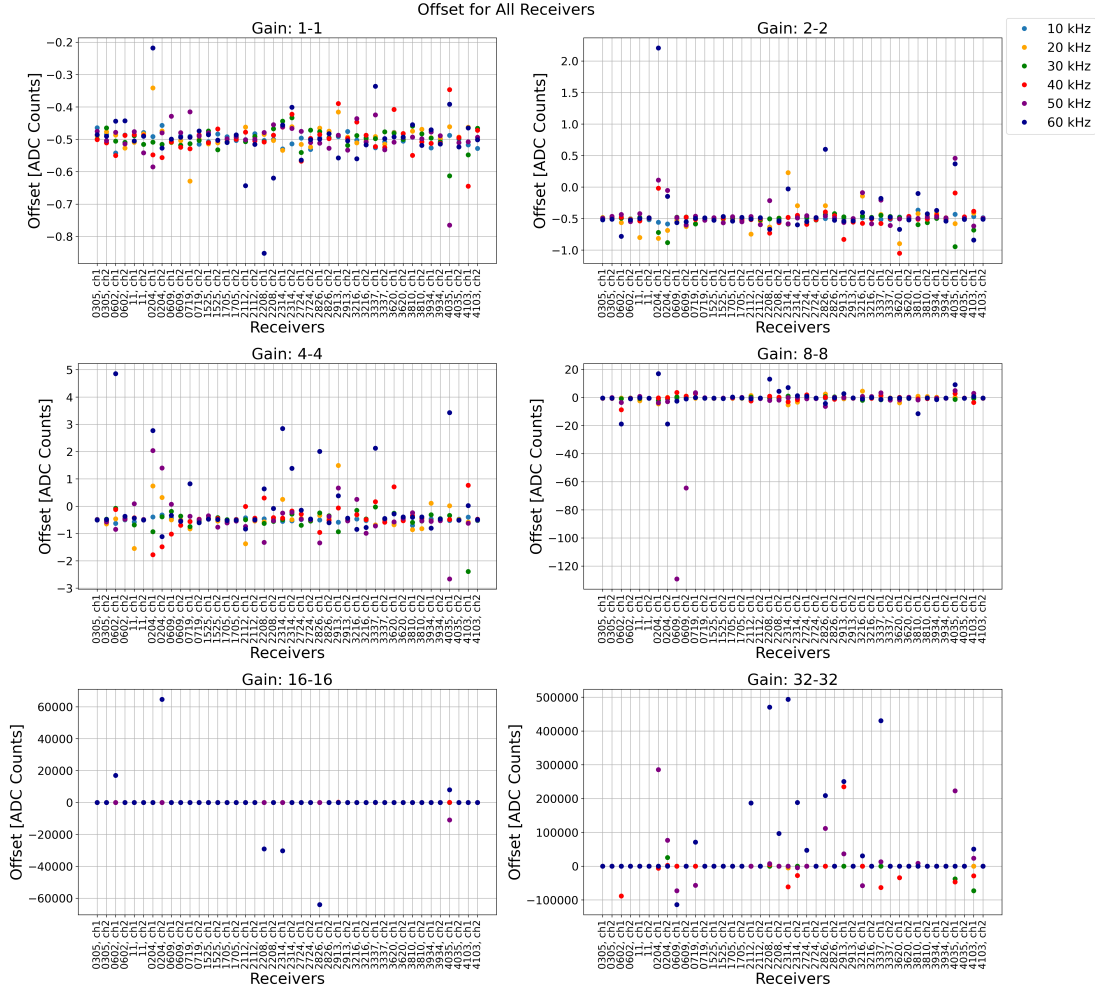


Figure 14: Plot of all offset values of all modules for all frequencies sectioned for every gain setting.

To investigate the correlation between higher gains or higher frequencies and a greater offset, I took the mean value of the amounts of every offset from every receiver and plotted it once as function of gain for different frequencies and once as function of the input frequency for different gains. Both plots are shown in Figure 15. The error for each point in both plots is the standard deviation that belongs to each mean value. The y-axis is scaled logarithmic in both plots.

Figure 15a shows clearly, that the offset strongly rises with higher gains. For gain 1-1 and 2-2 there is just a small difference between the different input frequencies and until gain 4-4 the offset is still lower than 1. Beginning with gain 8-8 the offset differs stronger between the different frequencies and for even higher gains this difference is growing even larger. It also looks like the highest input frequency is most affected by this. For 60kHz the offset for gain 8-8, 16-16, and 32-32 differs by several orders of magnitude. But until gain 8-8 with 40kHz the offset is around or even smaller than 1.

A similar picture is drawn by Figure 15b. You can clearly see that higher gains are coming with higher offsets, but also for higher frequencies, especially at the highest

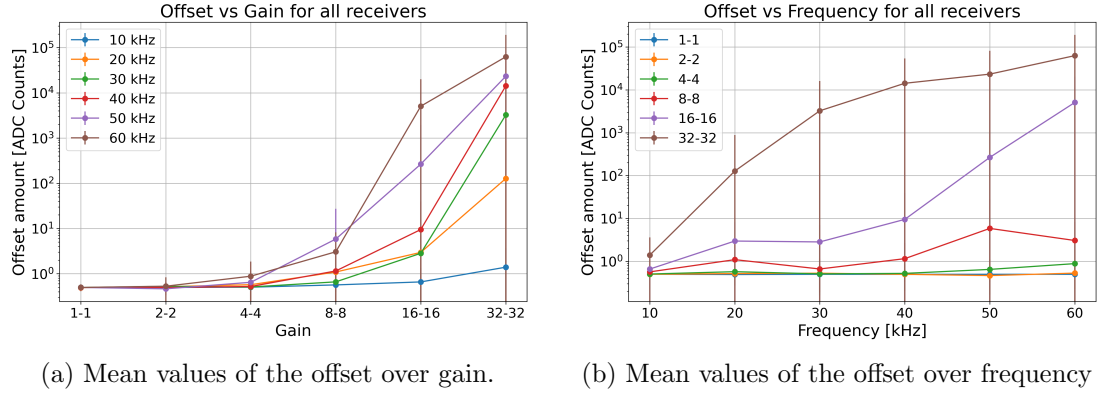


Figure 15: Plot of the mean value of the amounts of every offset from every receiver over the gain for different frequencies (a) and over the frequency for different gains (b).

gains, the offset gets stronger. It is also good to see, that for low gains the difference of the offset between the different frequencies is below 1.

In summary you can say, that the offset strongly differs with higher gains and depends on the input frequency to, especially for the highest gains. This means, if you want to have a stable and small offset, you should use smaller gains, because by using them the offset does not differ significantly with the input frequency.

4.1.2 Standard deviation

The next value I analyzed was the standard deviation as an indicator of the dispersion of the sinusoidal values of the input signal. Again for each receiver separately the standard deviation was plotted over the input frequency for different gains. The example of this plots from OM-3620 is shown in Figure 16. The other plots of the standard deviation

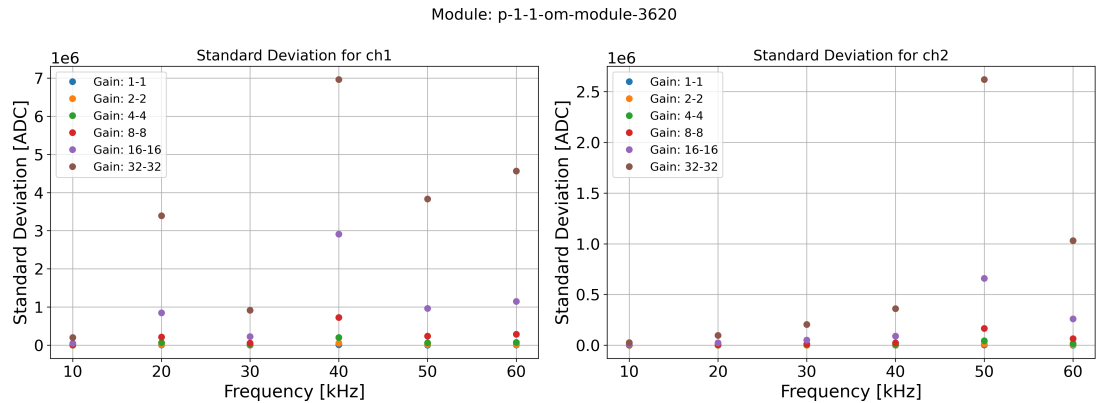


Figure 16: Plot of the standard deviation over the input frequency for all gain settings of both channels of OM-3620.

are included in Appendix B. I again also plotted the standard deviation for all modules in a summary plot divided in segments of the different gain setting, which is shown in Figure 17. From this plot you can tell, that for smaller gains the standard deviation is also small and for higher gains it gets higher, which makes sense, as the gain amplifies

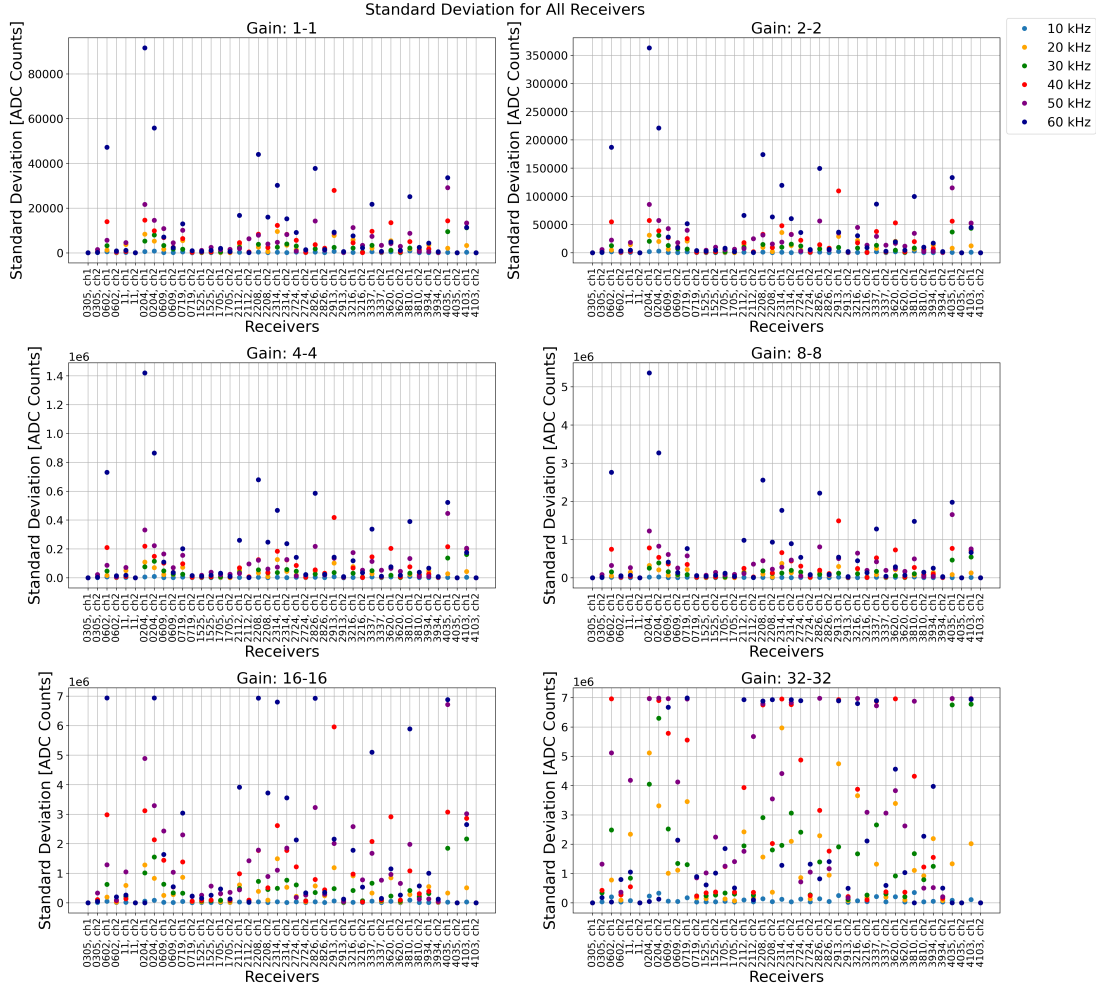
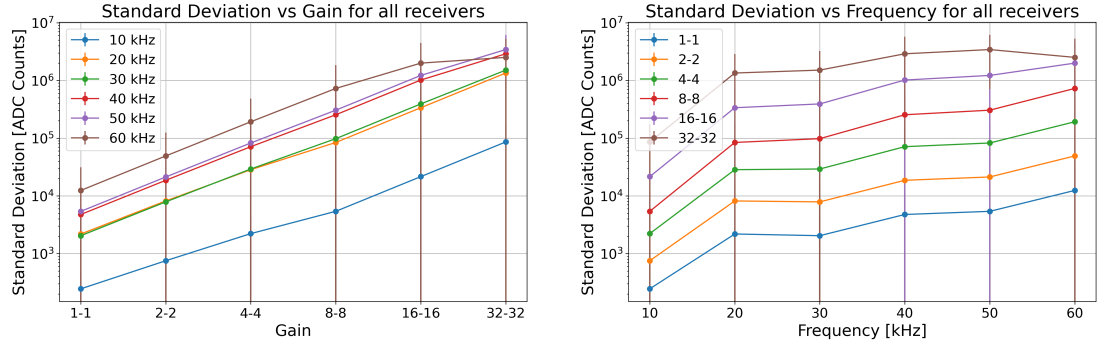


Figure 17: Plot of all standard deviation values of all modules for all frequencies sectioned for every gain setting.

the amplitudes of the initial signal. It also looks like the highest gains differ more significantly than the others again. And lastly the difference of the standard deviation across points of the same gain but different frequency seems quite small for small gains and significantly higher for higher gains. To check all of those assumptions for all receivers, I performed a plot of the mean value of the standard deviation of all receivers once over the frequency for different gains and once over the gain for different frequencies. Both plots can be seen in Figure 18. The errors are again given by the standard deviation from each mean value and again the y-axis is logarithmic scaled. The first thing you get from both plots is that definitely the standard deviation rises with higher gains, as was expected. The same applies in most cases for higher frequencies. But it also looks like the standard deviation rises quite equivalent for each frequency with every gain and vice versa, although every frequency and every gain rises in other orders of magnitudes in respective to each other.

It can therefore be said that the standard deviation increases with higher gains and input frequencies, but that this increase does not differ significantly when comparing



(a) Mean values of the standard deviation over gain.

(b) Mean values of the standard deviation over frequency

Figure 18: Plot of the mean value of every standard deviation from every receiver over the gain for different frequencies (a) and over the frequency for different gains (b).

different gains and frequencies across all receivers.

4.1.3 Peak-to-peak amplitude

Another value that has been analyzed is the peak-to-peak amplitude, which represents the magnitude of the signal. This value was again first collected for every module separately for all frequencies and gains and plotted as a function of the frequency. An example plot of OM-3620 is shown in Figure 19. For all other modules, peak-to-peak

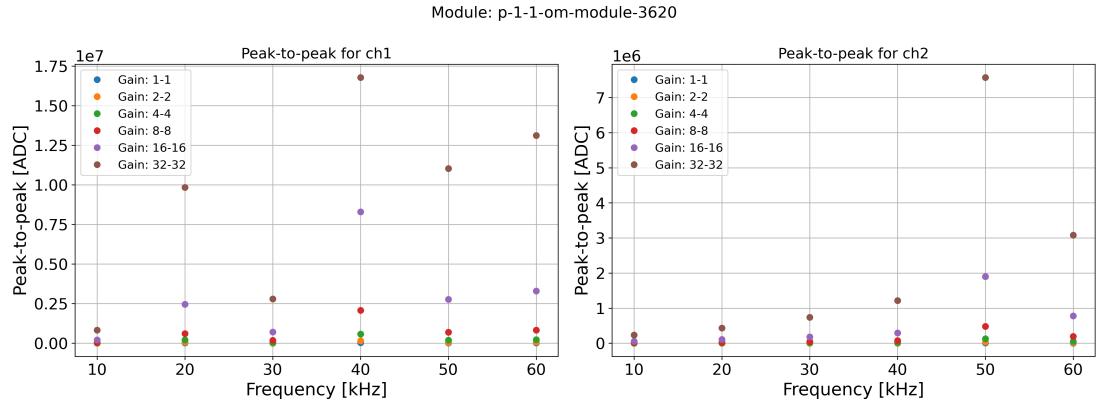


Figure 19: Plot of the peak-to-peak value over the input frequency for all gain settings of both channels of OM-3620.

plots are included in Appendix B. Here again, as for the standard deviation, you would assume the peak-to-peak amplitude will rise with higher gains because the amplitude of the signal gets amplified through the gain. Additionally, by plotting the peak-to-peak value over all modules segmented in the gain settings, you actually see a pretty similar picture to the standard deviation in Figure 20. And if you take the mean value of the peak-to-peak amplitude of all receivers for a specific gain and frequency and plot that once over the frequency for different gains and once over the gain for different frequencies you can actually see the assumed behavior in Figure 21. Here the errors are again given

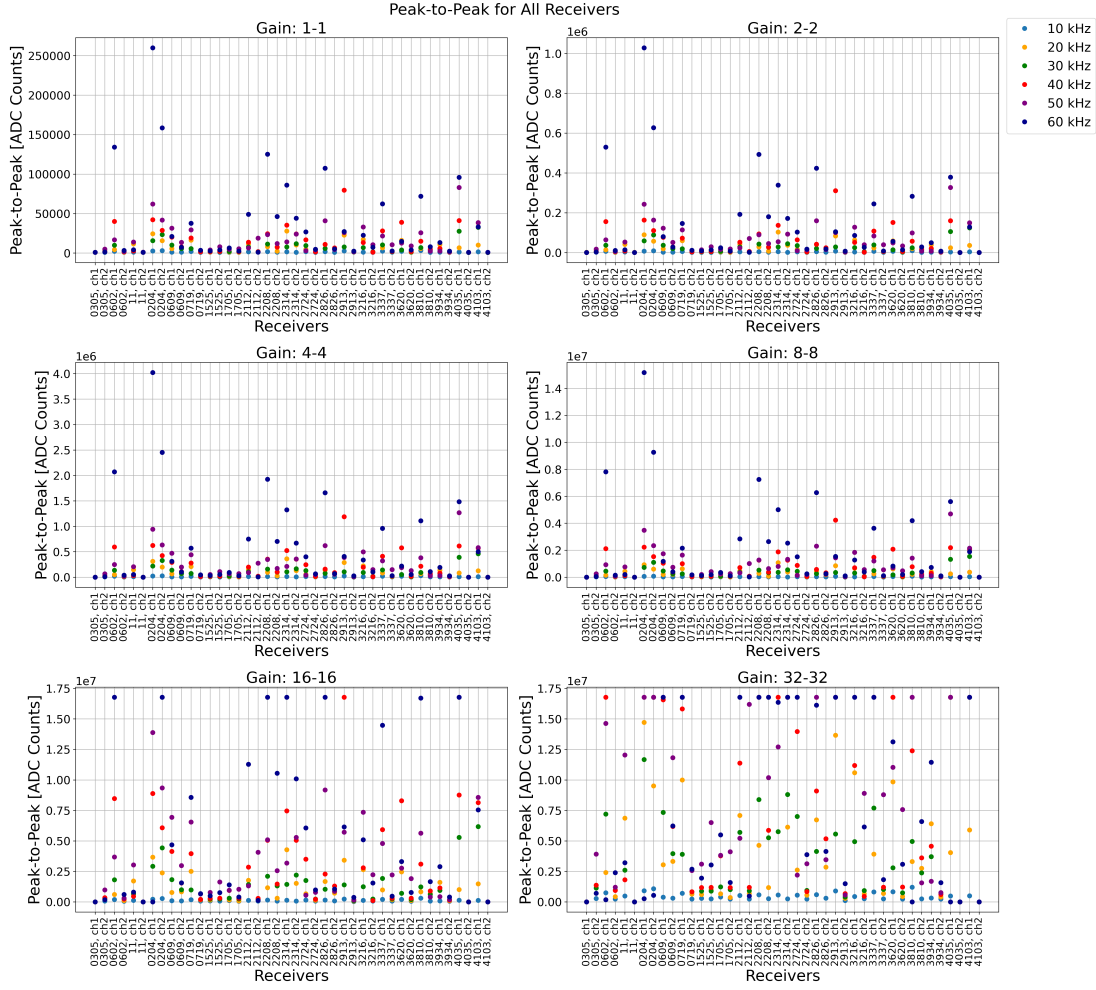
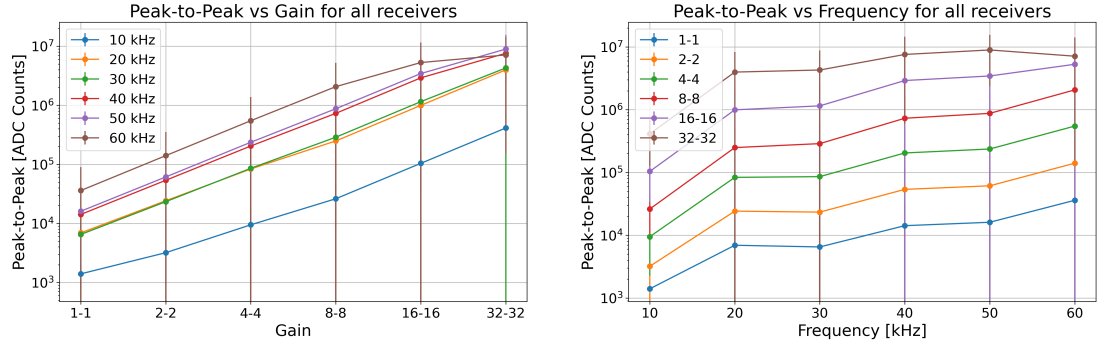


Figure 20: Plot of all peak-to-peak values of all modules for all frequencies sectioned for every gain setting.

by the standard deviation to each mean value. Figure 21 also looks a lot like Figure 18, which makes sense, because they both describe a value of amplitude of the same signals. Therefore, both depend on the same ways on the gain and input frequency. So the peak-to-peak amplitude is also stable and mostly equivalent in comparison between gains or frequencies. They are increasing with higher gains and frequencies, just with other orders of magnitude for different gains or frequencies.

4.1.4 Root mean square

The last value to characterize the time-based receiver properties is the root mean square representing the effective magnitude of the signal. To analyze this value, the RMS for each frequency and gain of one module was gained and plotted over the frequency. Figure 22 shows an example plot for OM-3620. The plots of the other modules are included in Appendix B. In this plot you can not tell any kind of dependence of the RMS to frequency or gain. To get a better picture of potential dependencies, I plotted the RMS for all modules segmented for each gain, which is shown in Figure 23.



(a) Mean values of the peak-to-peak amplitude over gain.

(b) Mean values of the peak-to-peak amplitude over frequency

Figure 21: Plot of the mean value of every peak-to-peak amplitude from every receiver over the gain for different frequencies (a) and over the frequency for different gains (b).

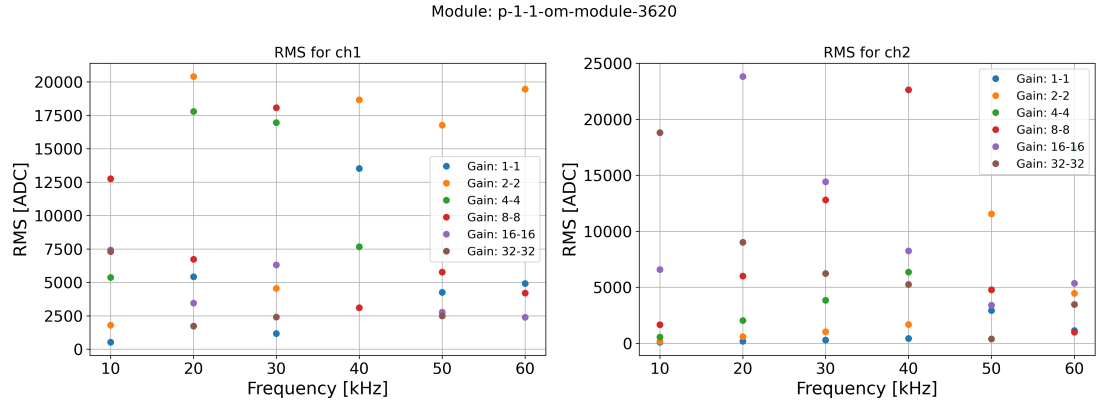


Figure 22: Plot of the root mean square value over the input frequency for all gain settings of both channels of OM-3620.

This plot shows an interesting behavior by comparing the 10kHz points and the 60kHz points from gain 1-1 and 32-32 as you can see that 10kHz points from gain 1-1, which have the lowest RMS, become the highest RMS points in gain 32-32 while for 60kHz the opposite is the case. Otherwise, the remaining points are spread out across a relatively wide range. The plot of the mean values of all root mean square values of all modules for specific gain and frequency settings once over the input frequency with different gains and once over the gain for different frequencies, which can be seen in Figure 24, should give a clearer picture to the distribution of the RMS. The errors are again determined by the standard deviation belonging to the respective mean value.

Figure 24a shows the RMS mean values as function of the gain. You can see, that for all frequencies above 10kHz the RMS rises with rising gain first until 2-2 or 4-4 and then drops again for higher gains. The graphs of those frequencies are really close to each other and are overlapping in parts. The 10kHz curve on the other hand has quite a different behavior, slowly rising at first, then rising stronger between gain 4-4 and 16-16 and finally rising a bit slower again at the end, but rising monotonic. The high-pass filter used in the receivers has a roll-off frequency of 10kHz [3]. It could be possible,

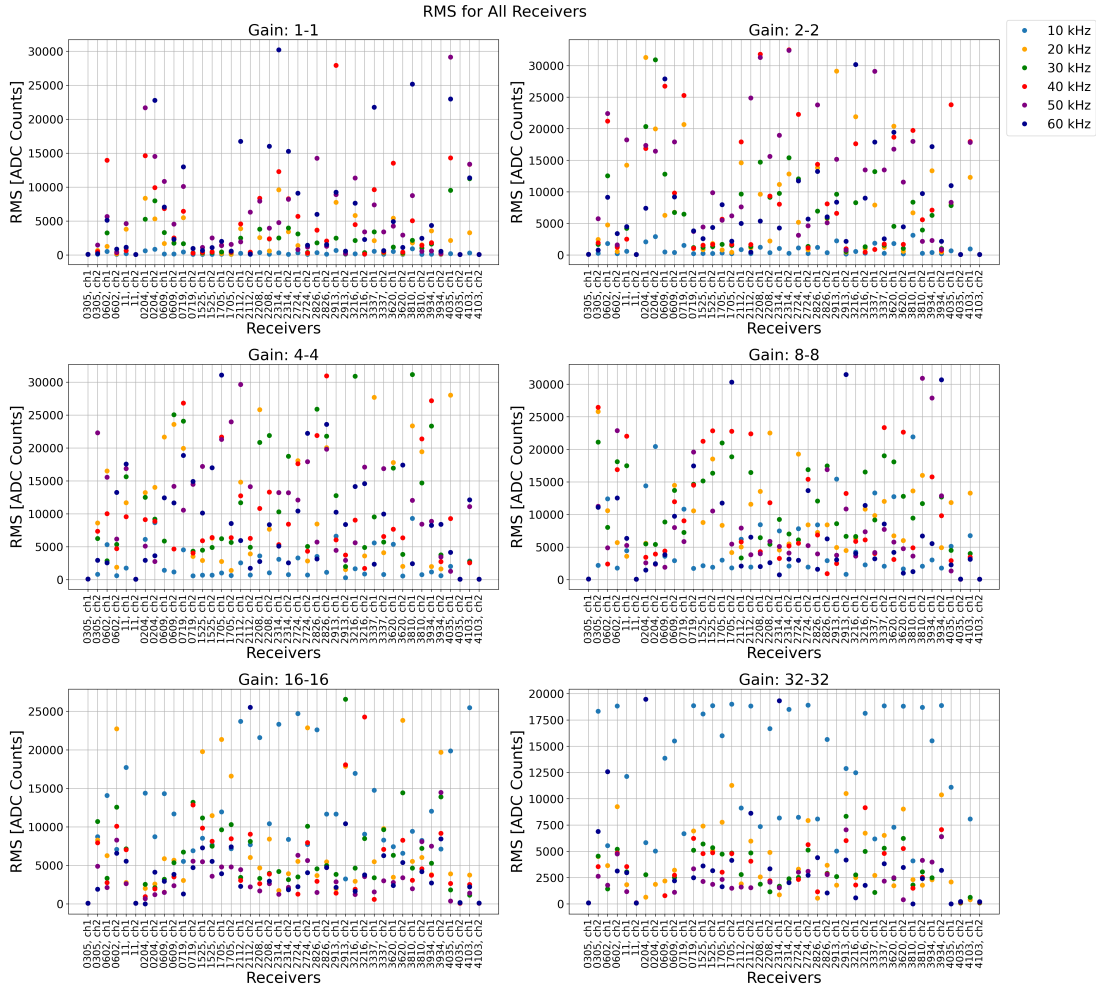
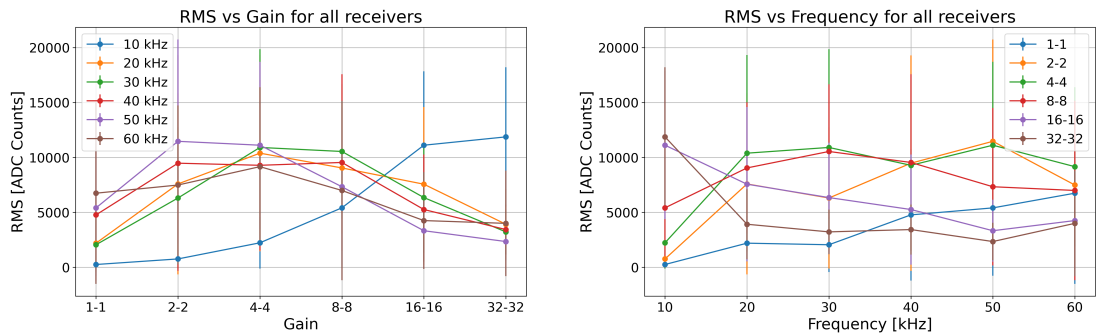


Figure 23: Plot of all root mean square values of all modules for all frequencies sectioned for every gain setting.



(a) Mean values of the root mean square over gain.

(b) Mean values of the root mean square over frequency

Figure 24: Plot of the mean value of every root mean square value from every receiver over the gain for different frequencies (a) and over the frequency for different gains (b).

that with increasing gain this frequency gets shifted down slightly, which would explain the strong rise of the RMS for higher gains.

So for most of the frequencies you get the highest root mean square at gain 2-2 or 4-4 and the lowest on gain 1-1 or 32-32, but as the 10kHz curve rises monotonic, the lowest RMS is at 1-1 and the highest at 32-32.

The graphs in Figure 24b are even more overlapping. But you can clearly see, that for the high gains of 16-16 or 32-32 the root mean square gets rather smaller or stays nearly constant when going to higher frequencies, whereas the lower gains tend to rise or stay constant. So for lower gains the lower frequencies have the lowest root mean square values and for the highest two gains the lowest value is at higher frequencies.

4.2 Frequency-based receiver properties

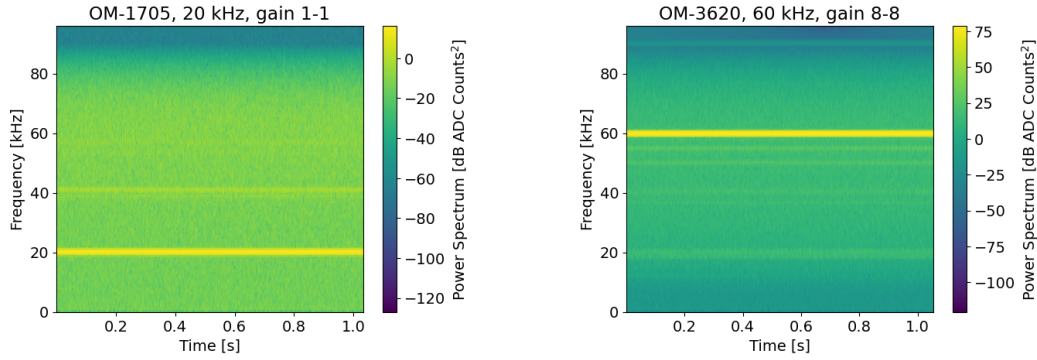
In the second step of the analysis, we examine the signal measured by the receiver in the frequency domain. In this context, there are two parameters in particular that are of interest and can be derived from the test: the frequency response of the receivers and the amplitude of the frequency peak.

4.2.1 Frequency response

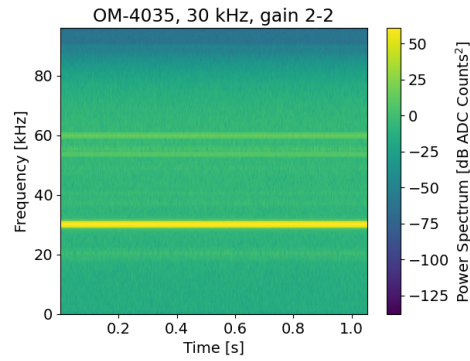
Knowing the frequency response of the receivers is particularly important for using the acoustic systems in P-ONE. This tells you, how well each receiver can resolve the frequency information of the incoming signal. To get this information, my first step was to plot the spectrogram of all test signals for all modules, gains and initial frequencies as described in subsection 3.3. For all of the spectrograms, a N_{FFT} value of 256, a noverlap value of 128 and hann windowing was used. Figure 25 shows some examples for different measurements. In all three spectrograms you can see a line with most magnitude around the respective input frequency, which is a first indicator for the fact, that the measurement and the receiver worked. This line is quite wide though, which is an effect of the used N_{FFT} and noverlap settings. You can also see resonances at other frequencies that are not quite as strong. The third thing, you could assume from this first plots, is that the signal-to-noise ratio gets better with higher gains. The magnitude scale is different for every plot and you can see that the magnitude of the prominent line is for the plots with higher gains higher than for the gain 1-1 plot, where the prominent line has just slightly more magnitude than the noise.

As a next step, these spectrograms get averaged over the time like described in subsection 3.3. This gives us the power spectrum peaks shown in Figure 26. You can see all three prominent peaks at the respective initial frequencies as well as the peaks of lower magnitude from the background, for example the peak near 50kHz in Figure 26b or the peak near 20kHz in Figure 26c.

To get the peak frequency of the prominent peak as the value of interest, my first intension was to perform a Gaussian fit with linear background on the data points as described in subsection 3.3 and use its μ -value as the wanted peak frequency. This fit is not physically motivated, it was just a first idea to describe the peak. The Gaussian fit is the green line in the plots of Figure 26. As you can see, the fit works quite well in Figure 26a because the background is quite linear, but especially in Figure 26b the linear background description was not suitable at all. It looked more like there was a second, bigger Gaussian peak that described the background of the data. So my second try was



(a) OM-1705, gain 1-1, 20kHz input frequency, receiver 1. (b) OM-3620, gain 8-8, 60kHz input frequency, receiver 1.



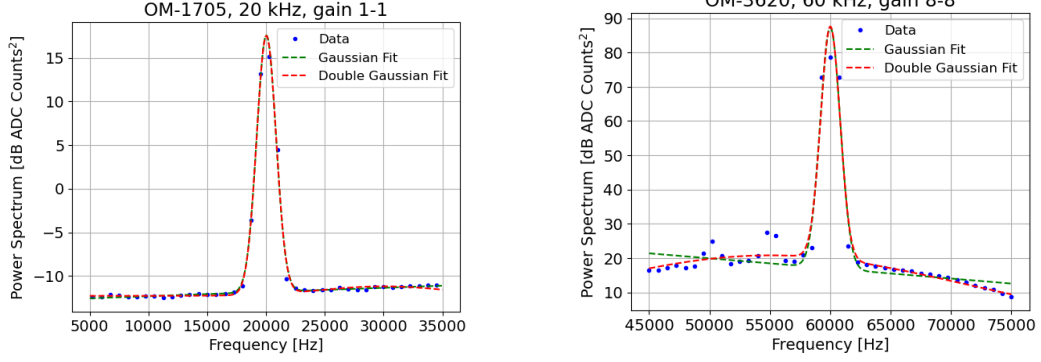
(c) OM-4035, gain 2-2, 30kHz input frequency, receiver 1.

Figure 25: Spectrograms of three different measurements.

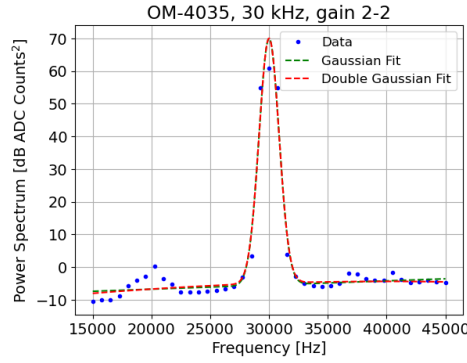
a double Gaussian fit with constant offset as also described in subsection 3.3 with one peak describing the frequency peak and the other one describing the background of the data. As you can see, the double Gaussian fit (red) worked way better for describing the background of Figure 26b whereas in Figure 26a and Figure 26c it made just a small difference, but in total it suited the form of the data better, although one must say, that the frequency peak in all three cases are the same for Gaussian and double Gaussian fit and as this is the spot of interest the change from Gaussian to double Gaussian fit is mostly helpful to ensure a more adaptable fit on the data points because the second Gaussian peak describes the background better.

But there were now some aspects that made working with the spectrogram more difficult. At first, as you can see in all plots of Figure 26, the peaks are quite wide which is because of the effect that you lose frequency resolution when plotting the frequency peak with the spectrogram as described in subsection 3.3. The second problem is that for every double Gaussian fit different kinds of bounds have to be made that all have to be quite wide for the background peak. This led to a lot of difficulties by performing this plots for all measurements. And because the periodogram is the better option for constant signals, as also described in subsection 3.3, I decided to switch from spectrograms to periodograms.

As I mentioned in subsection 3.3, a periodogram with scaling = spectrum shows the



(a) OM-1705, gain 1-1, 20kHz input frequency, receiver 1. (b) OM-3620, gain 8-8, 60kHz input frequency, receiver 1.



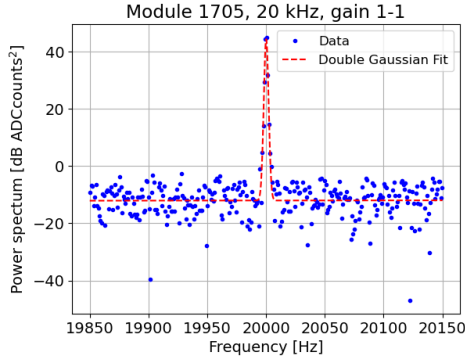
(c) OM-4035, gain 2-2, 30kHz input frequency, receiver 1.

Figure 26: Spectrogram peaks of the averaged three example spectrograms of Figure 25.

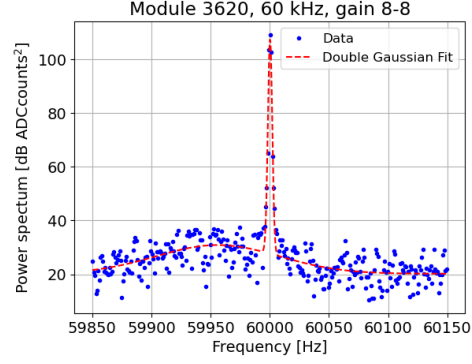
power spectrum of the signal. It has the most magnitude at the frequency that is most represented in the spectrum. For this reason, the periodogram of each measurement should show a sharp peak at the initial frequency. To get a better picture of how a periodogram of the measured signals of the MINT with a sampling rate of 192kHz and a duration time of approx 1s looks like, the periodogram of the same three example measurements as in Figure 25 were performed with hann windowing, scaling = spectrum and $N_{\text{FFT}} = N$. They are shown in Figure 27, as well as a double Gaussian fit on the peaks.

The first thing to recognize with those periodograms is that the peaks are quite more narrow than with the use of spectrograms. In Figure 27b the second Gaussian peak fits again the course of the data points quite good. But because of the higher N_{FFT} there are now more data points in the periodogram and the points outside the peak are actually quite randomly distributed. Additionally, the double Gaussian fit did not seem like the best possibility to get the peak frequency when looking just at the peak region. This is why I decided to also try the Lorentzian fit with constant background empirically, as described in subsection 3.3.

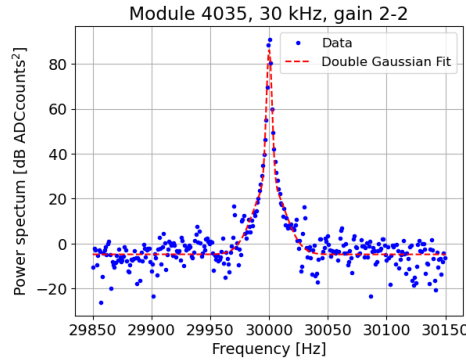
For the next step, I first looked at a specific receiver and gain setting for all frequencies to get a better differentiation of the two fits. For this instance, Figure 28 shows the periodograms of the optical module 3620 receiver 1 for gain 8-8. For every fit, the χ^2



(a) OM-1705, gain 1-1, 20kHz input frequency, receiver 1.



(b) OM-3620, gain 8-8, 60kHz input frequency, receiver 1.



(c) OM-4035, gain 2-2, 30kHz input frequency, receiver 1.

Figure 27: Periodogram peaks of the averaged three example spectrograms of Figure 25.

value described in subsection 3.3 is also been calculated to compare the fits with each other. For this first example, it looks like the double Gaussian fit suits the data better because the χ^2 value is smaller for every frequency. But one thing to notice is that there are actually examples where the Lorentzian fit gets closer to data of the peak, like for 10kHz or 30kHz, where the peak of the Lorentzian fit gets closer to the upper data points. In other examples, e.g. for 40kHz and 60kHz the Lorentzian fit is higher than the upper data points whereas the double Gaussian fit is slightly lower. For an initial comparison of both fits, all periodograms of OM-3620 with both fits in a range ± 50 Hz around the input frequency have been performed and the peak frequency, the σ value and the χ^2 value were taken for a further comparison and analysis of the frequency response.

So the fitted peak frequencies of OM-3620 channel 1 were plotted versus the initial frequencies of the signal for each gain setting. The σ value plotted as y-error in this plots, indicates how well the peak frequency can be resolved. Figure 29 shows the results.

You have to differentiate two different types of information in Figure 29. First of all, the blue and yellow points are the peak frequencies of the receiver from the power spectra. As you can see, they lie in each case more or less on the ideal line. This line resembles the ideal case, where the frequency responses equal the initial frequencies. In all of the

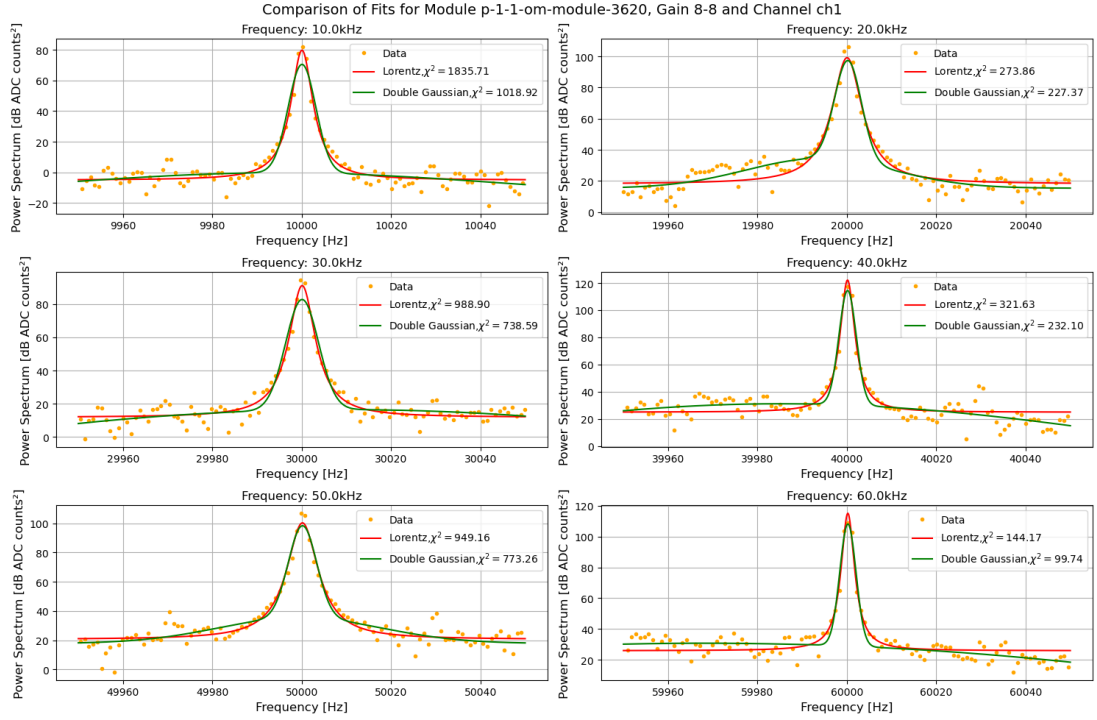


Figure 28: Periodograms of the optical module 3620 receiver 1 for gain 8-8 for all frequencies with Lorentzian and double Gaussian fit.

subplots, the peak frequency of both fits almost perfectly match the initial frequency, which is resembled in the frequency deviation. This deviation resembles the difference between the peak frequency and the input frequency. Because the background peak of the double Gaussian fit is included, it is hard to tell the actual deviation of the peak frequency from the ideal line in this plot, but it is getting clearer in another plot later on. The residuals in this plots are help to differentiate the two peaks of the double Gaussian fit.

To really characterize the peak frequency of the double Gaussian fit, it is of high importance that we can distinguish between the actual peak frequency and the background peak. Because the background peak does not need to match the initial frequency, it can be assumed, that there are cases, where this peak is further away from the initial frequency. This is the reason, why there are some background peak points (green), that deviate quite more from the ideal line than the other points. The fact, that those points are all green, gives us the information, that the distinction of the frequency peak and the background peak works.

A better look on how well the measured data resolve the initial frequency is given in Figure 30, again for receiver 1. This plots show the peak frequencies versus the initial frequencies, but this time for all gain settings in one plot, but separated in every fitted peak. You can see that for all three plots the peak frequencies are again more ore less lying on the ideal line for every gain setting. But this time, it is clearly visible that for the Lorentzian fit and for peak 1 of the double Gaussian the frequency deviation is really small, for the double Gaussian peak its a maximum of around 0.25Hz, for the Lorentzian fit it is even smaller with a maximum of around 0.2Hz. The deviation of

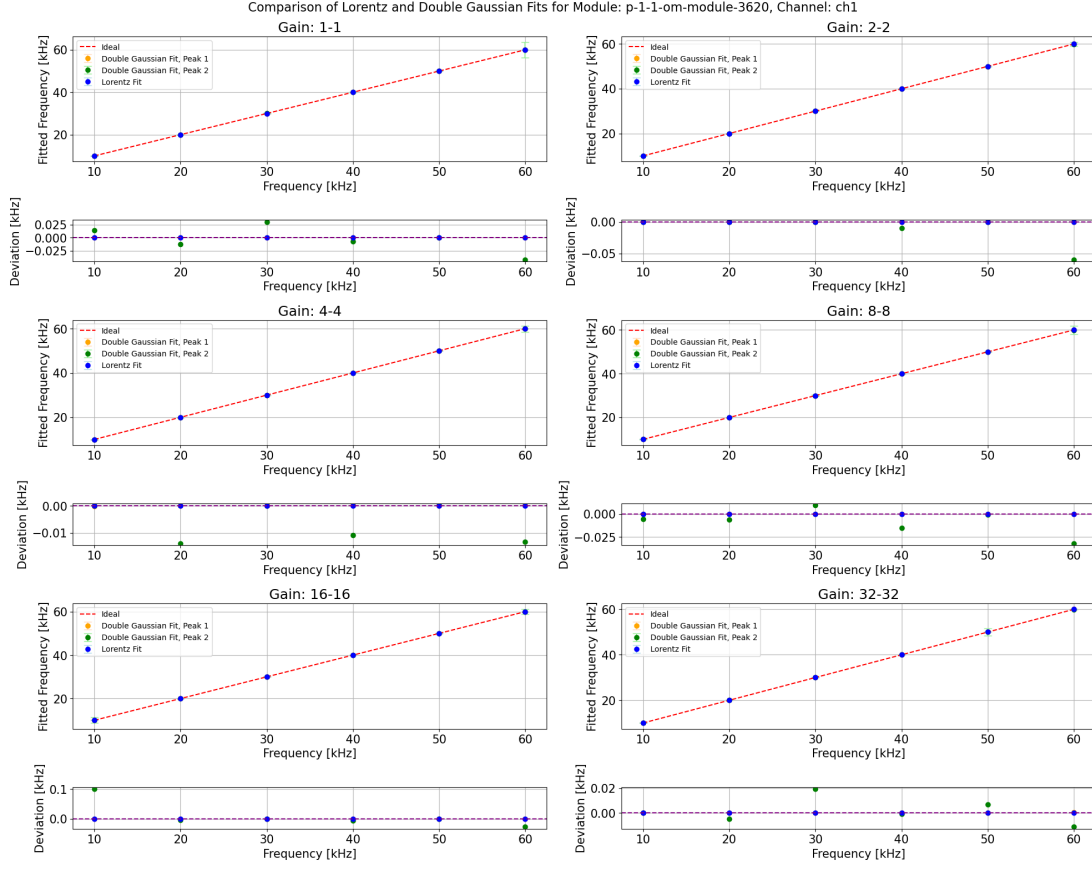


Figure 29: Fitted peak frequencies of OM-3620 receiver 1 gained with every fitted peak of both fits with their respective σ values as an indicator of resolution versus initial frequency for every gain setting and residuals.

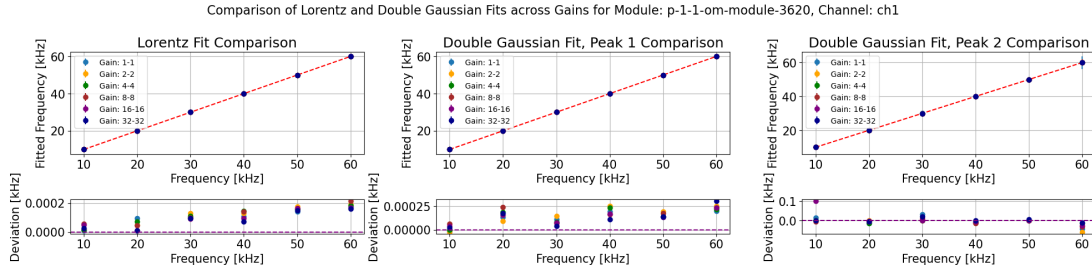


Figure 30: Peak frequencies with respective σ values versus the initial frequencies of OM-3620 receiver 1, separated in the different fitted peaks. Peak 1 of the double Gaussian resemble the frequency peak of the periodogram, peak 2 the background.

the background peak of the double Gaussian fit is once again much higher, which again gives the information that the distinction between the peaks is working.

To now compare the fits and find a way to declare which fit does resolve the frequency peaks better, I also plotted the χ^2 values of both fits for the initial frequencies separated by each gain setting. Figure 31 shows the example, again of receiver 1 of OM-3620. As you can see, in most of the cases the χ^2 value of the double Gaussian fit is smaller than

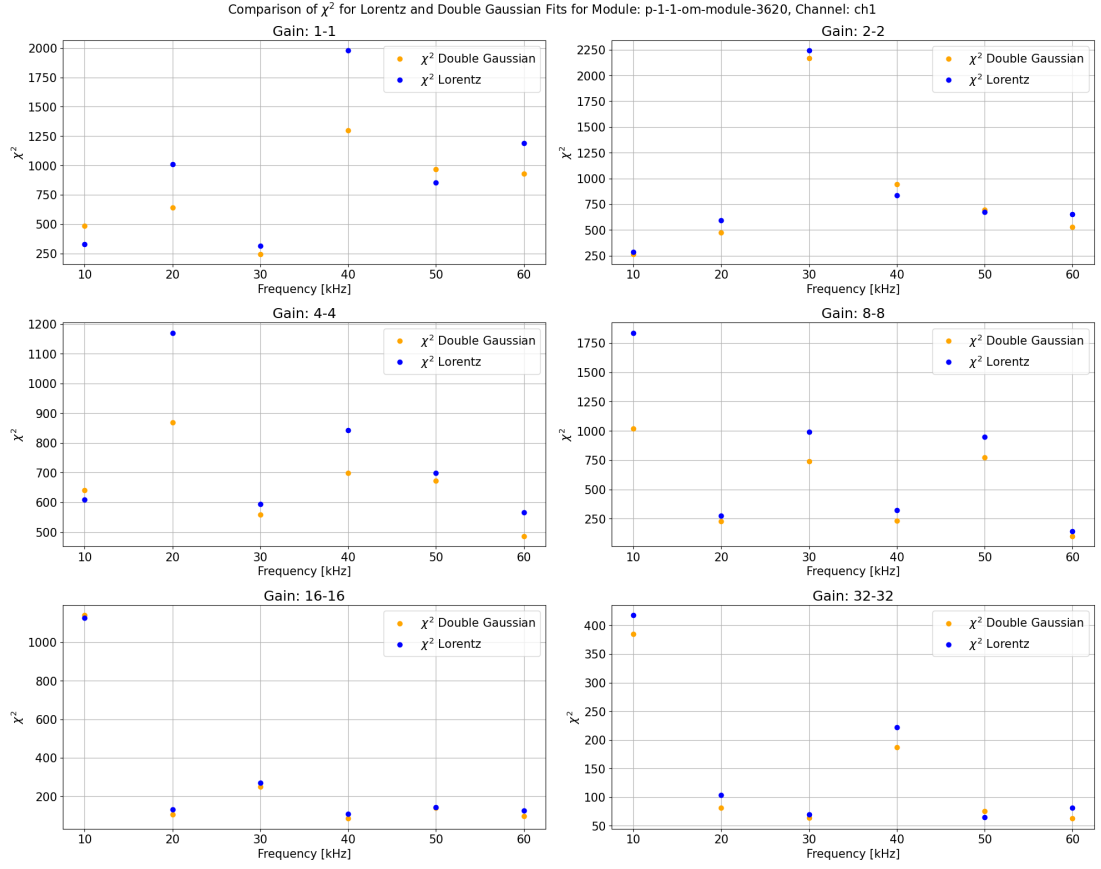


Figure 31: χ^2 values of both fits versus input frequency, separated for every gain setting.

the Lorentzian, but there are also some examples with smaller Lorentzian χ^2 values and some examples where both fits are really close to each other. To get a well-founded decision on which fit performs better later on, the χ^2 values of all receivers have to be compared later on.

As can be seen, you could actually find the frequency response of all receivers for all gain settings and initial frequencies with both of these fits, assuming that the fits work as well as in the example of OM-3620 for all the other modules, even though both fits are only empirically motivated by data because of the usage of the hann window.

The biggest issue of the use of those fits is the second Gaussian peak that resembles the background. On one hand, it is until this point the best way to describe the background noise of the periodograms, but on the other hand, the bounds of the fit parameters for this peak have to be really wide. If these bounds are too narrow, the fit will not work, but if they are too wide, it can happen that the peak gets fitted on another subpeak instead of the complete background. This leads to the fact that this bounds differ a lot for each module. But if the background gets removed, there would be no more need of a second Gaussian peak.

As I mentioned earlier, there were measurements performed for no initial frequency in the MINT. This measurements can be used to get every periodogram without its background noise. This measurements were done once for every receiver in every gain setting,

so that for a single receiver and a specific gain setting one background measurement was performed. These measurements resemble the background noise of all measurements of the receiver with the specific gain setting. For this instance, both periodograms have to be generated with the same FFT length N_{FFT} . For reasons I explained in subsection 3.3, the smaller number of data points of both measurements was used as N_{FFT} . Then, the periodogram with the measurement of interest got subtracted by the respective background periodogram

$$P_{\text{signal}} = P_{\text{measure}} - P_{\text{noise}} \quad (26)$$

and only after that the resulting periodogram got converted in dB units. This is possible, because the power spectrum is proportional to the FFT squared $|X_{\text{measure}}|^2$. The FFT is given by $X_{\text{measure}} = X_{\text{signal}} + X_{\text{noise}}$ because of the linearity of the FFT. So the power spectrum is proportional with

$$|X_{\text{measure}}|^2 = |X_{\text{signal}}|^2 + |X_{\text{noise}}|^2 + X_{\text{signal}}X_{\text{noise}}^* + X_{\text{signal}}^*X_{\text{noise}} \quad (27)$$

and if signal and noise are uncorrelated, you get $P_{\text{measure}} \approx P_{\text{signal}} + P_{\text{noise}}$.

An example of a periodogram with its background versus just the background is shown in Figure 32. Now we can do the same plots as in Figure 29, Figure 30 and Figure 31

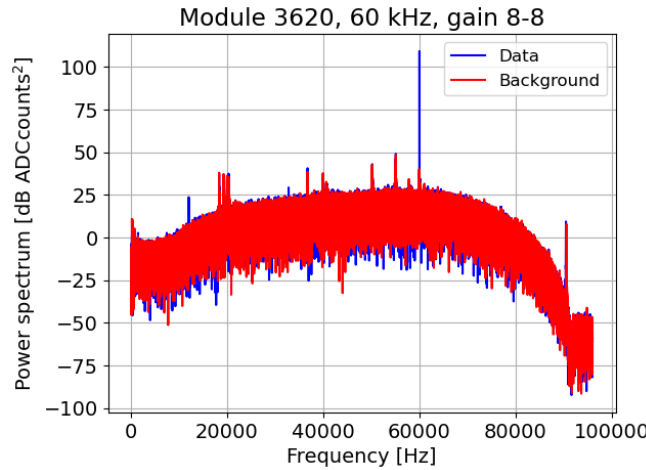


Figure 32: Complete periodogram for gain 8-8 recording background data (red) and data with an input signal of 60 kHz (blue).

again without the background and with just the pure data. And because I removed the background, there is no motivation to continue with a double Gaussian fit, so the final fit comparison was done between a Lorentzian fit and a Gaussian fit, which now just resemble the periodograms peaks.

To get a direct comparison with the frequency response plots of OM-3620 receiver 1, the same plots for the same receiver were performed, but without the background this time and with a Lorentzian and a Gaussian fit. The results can be seen in Figure 33, which shows the frequency response separated by gain, Figure 34, showing the frequency response separated by fit, and Figure 35, where you can see the χ^2 value of both fits.

Figure 33 and Figure 34 show a pretty similar picture to Figure 29 and Figure 30, although it is now clearly visible, that both fits get similar frequency deviations for each

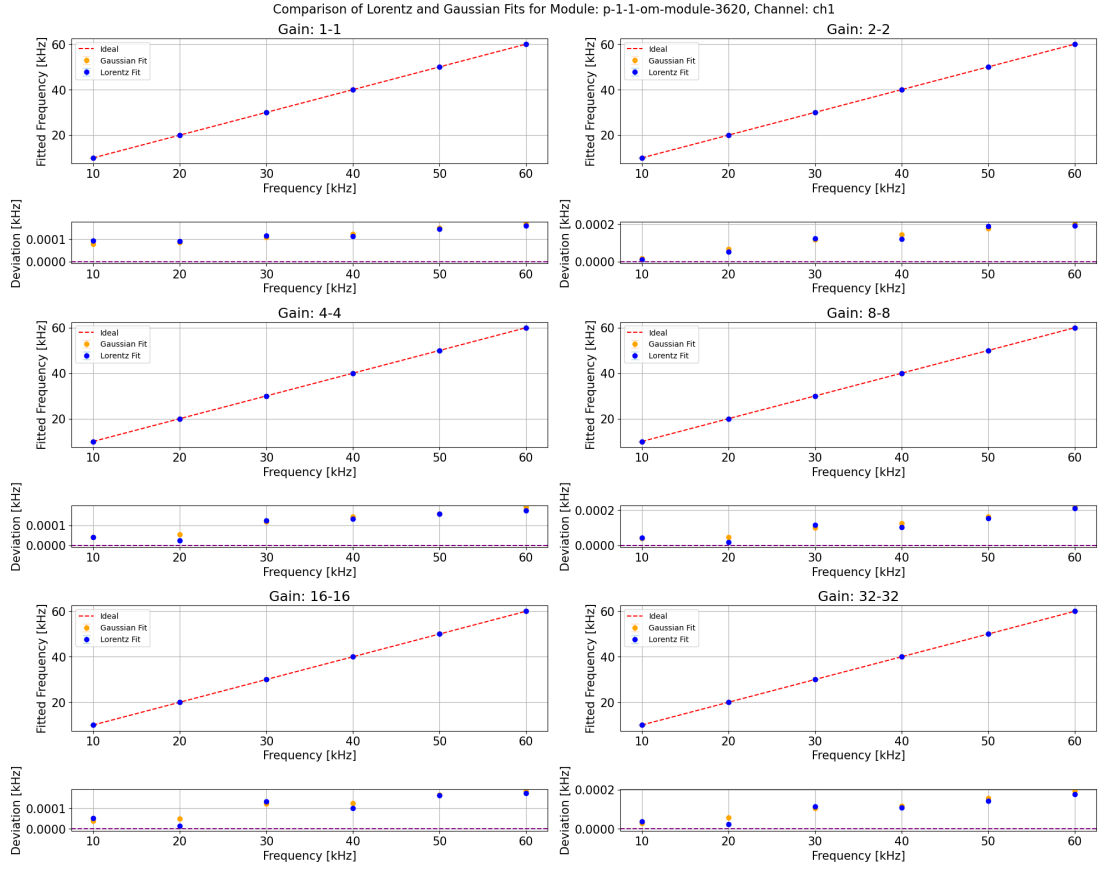


Figure 33: Fitted peak frequencies gained with the fitted peaks of both fits with their respective σ values as an indicator of resolution versus initial frequency for every gain setting and with the residuals in addition.

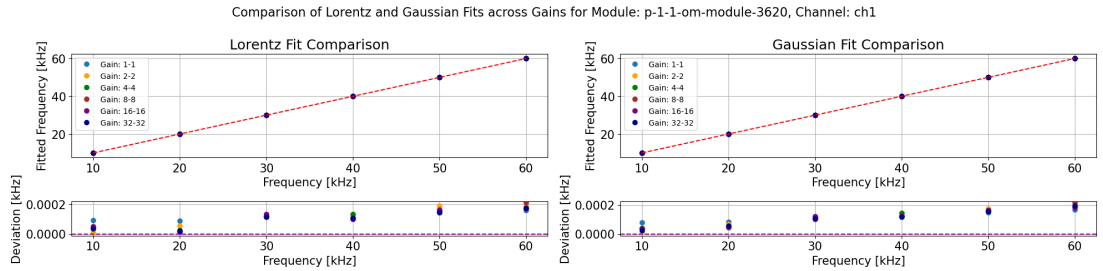


Figure 34: Peak frequencies with respective σ values versus the initial frequencies, separated in the different fits.

peak frequency. This results show that OM-3620 channel 1 as test receiver actually got a quite accurate frequency response. So you could assume that it is with both fits possible to characterize each receiver for a good summary as a last step.

Figure 35 on the other hand shows a quite different picture without the noise than with it. It seems like the Lorentzian fit got a lower χ^2 value in most cases. The double Gaussian fit had smaller χ^2 values in most of the cases, because it had one peak that just resembled the noise and fitted better on the background data, which the Lorentzian

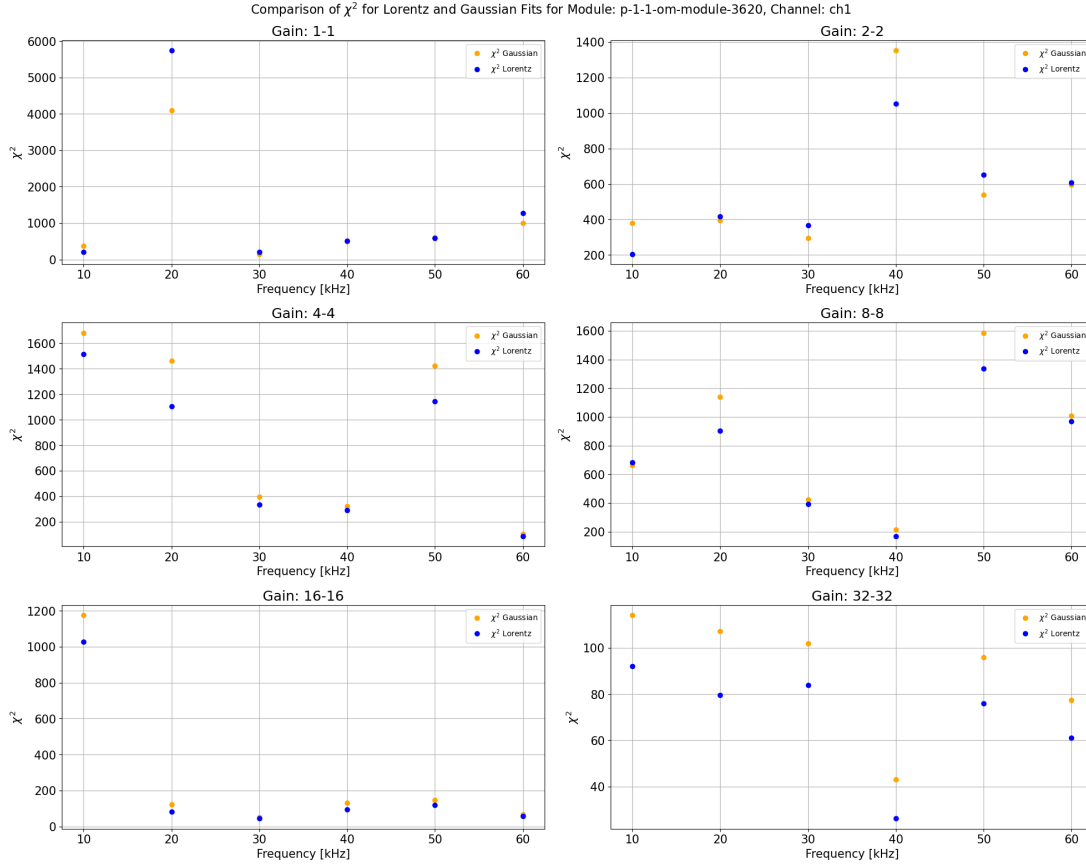


Figure 35: χ^2 values of both fits versus input frequency, separated for every gain setting.

did not have. Now that the noise is removed, the Lorentzian seems to work better. To determine which fit actually fits the data better, I created a comparison of all χ^2 values for both fits. For this instance, I collected the χ^2 value for each fit of all receivers for each specific combination of input frequency and gain and took the mean value of those values. As there are 36 possible combinations of initial frequency and gain, this leads to 36 mean χ^2 values per fit. And each mean value, representing a specific gain-frequency pair, was compared between fits in terms of which one is smaller. As a result, the Lorentzian fit had a smaller χ^2 mean value for 28 gain-frequency pairs, the Gaussian fit just for 8. This is why, at this part of the analysis, I decided to use only the Lorentzian fit for the final steps of the evaluation.

But until this point, hann windowing was used for better signal-to-noise ratio. Also, the Lorentzian was just picked empirically. If we want to use a physically motivated fit, we have to use the logarithmic Lorentzian fit as described in Equation 21 and therefore also use a boxcar window, because the hann window changes the initial signal and therefore the FFT, which leads to a different function in the end. As an example, Figure 36 shows the periodogram without background noise of OM-3620 receiver 1 with 60kHz input frequency and gain 8-8 with boxcar windowing and the Lorentzian fit on the data. As can be seen, the Lorentzian curve now reflects the trend of the actual data much more accurately. This setting allows the most accurate determination of the frequency response.

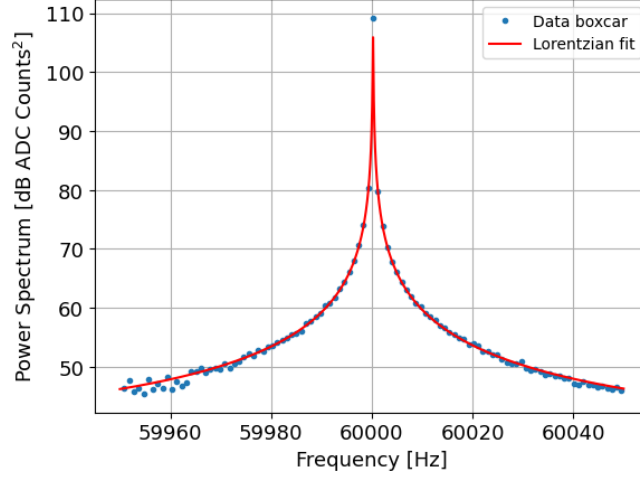


Figure 36: Periodogram of OM-3620, receiver 1 with 60kHz input frequency, gain 8-8 and boxcar windowing plus a Lorentzian fit.

To achieve this, for starters the peak frequency of every measurement with every receiver in every possible setting was gained. To get a first glance at the frequency responses, for every receiver a plot was performed that shows the gained peak frequency of the power spectrum versus the input frequency for every gain setting and the frequency deviation in addition. Figure 37 shows this plot as example.

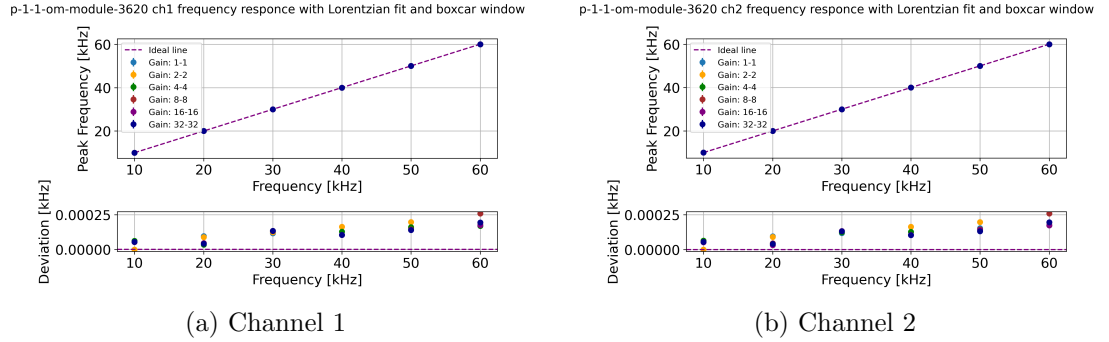


Figure 37: Frequency response of OM-3620 (both channels) for all gains.

As can be seen, the peak frequencies deviate very little from the expected frequency amount. You can also see that the frequency deviation seems to get bigger for higher initial frequencies, but stays below or around 0.25Hz. Another aspect that stands out is that for both channels the frequency responses and the deviations look quite similar, differing by only a few points, which is also good assuming the same test conditions for both receivers. In summary, OM-3620 resolved the initial frequency accurately, the frequency plots for the other modules are included in Appendix B.

To look at how the frequency response depends on the initial frequency and the gain over all modules, a plot was performed using the mean value of the frequency responses of every receiver once for a specific gain setting plotting it versus the input frequency and once for a specific frequency setting plotting it versus gain. The error bars are given by the standard deviation to those mean values. The two plots are shown in Figure 38.

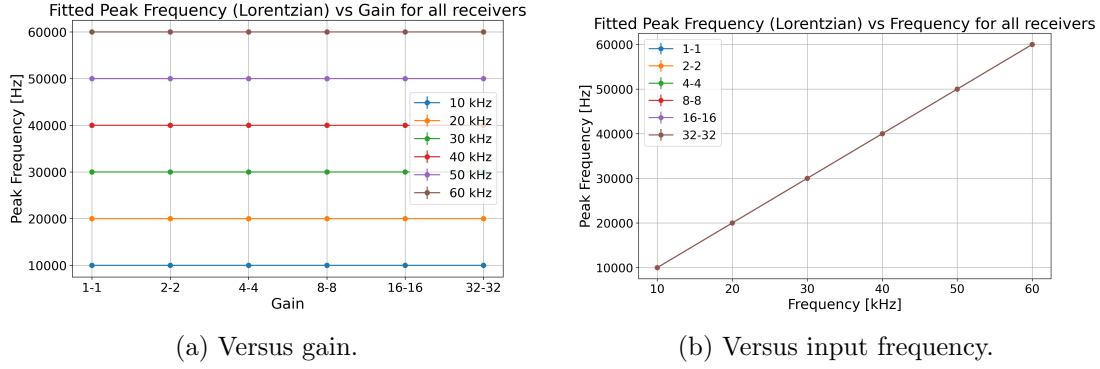


Figure 38: Mean values of the frequency response over all receivers for a specific frequency plotted over gain (a) and for a specific gain plotted over the input frequency (b).

As expected from the plots of the frequency response for a single module as in Figure 37, you can not see any clear difference using different gains in terms of resolving the frequency peak in both plots of Figure 38. But you can clearly see that averaged over all receivers the peak frequency of the Lorentzian fit reflects its respective initial frequency accurately. And now we can also look at the frequency responses of all receivers at once. For this instance, a plot was performed, that contains every receiver on the x-axis and a frequency scale on the y-axis. The plot is selected in each gain setting and for one gain setting, the frequency responses of each receiver were plotted separately. This was done by plotting the frequency response of each input frequency individually. In addition, the plot shows the frequency deviations from the initial frequency. The error bars are again the γ parameter of the Lorentzian fit as an indicator of how well the frequency peak can be resolved. The plot is shown in Figure 39.

The most important point of this plots is the fact that all frequency responses shown in this plots resemble their respective input frequencies accurately, with all deviation subplots have their maximum values around 0.5Hz, which resembles a very accurate resolution of the given input frequency of the working receivers.

But in between the frequency responses of the working receivers, there are some gaps in this plot. These gaps belong to the error receiver measurements (Table 1). The measurements with no output signal also gave no frequency responses in Figure 39. The other missing points belong to the other error receivers. CAL-0305 channel 1 and OM-hs-11 channel 2 should not have any frequency peaks, but they have a output signal as well as a power spectrum. The two receivers OM-4035 channel 2 and OM-4103 channel 2 have missing frequency response points especially for lower gains and lower frequencies. This comes from the fact, that the periodograms of this receivers show no clear peaks for lower gains and small frequency peaks for higher gains. As an example for this behavior, Figure 40 shows the 40kHz measurement of receiver OM-4103 channel 2 for gain 2-2 and gain 32-32.

As can be seen in Figure 40a, a Lorentzian fit would return a peak frequency, although there is no actual peak to fit on. This is why I decided to give the fit a lower amplitude bound of 10 ADC Counts², which drops the number of false frequency responses in Figure 39. But receiver 1 of CAL-0305 and channel 2 of OM-hs-11 still have frequency responses at higher gains and frequencies. I although decided, not to set a higher bound,

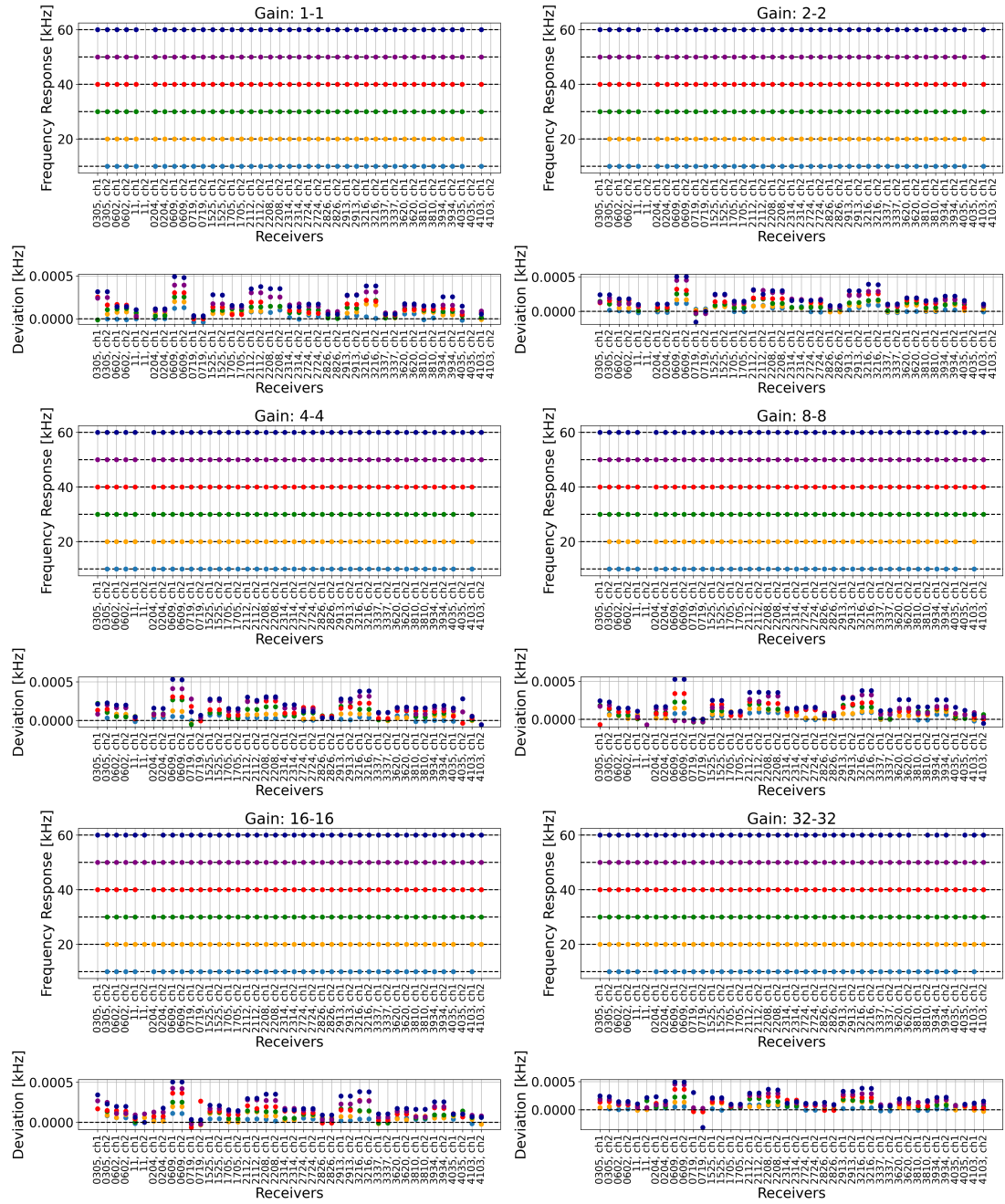


Figure 39: Frequency response of all receivers sectioned in different gain settings and separated in each input frequency, the frequency deviations in addition. Each color represents an input frequency (light blue: 10kHz, orange: 20kHz, green: 30kHz, red: 40kHz, purple: 50kHz, dark blue: 60kHz)

so that the measurements with small peaks not get excluded.

Another interesting fact is shown in the frequency deviation. It often looks like two receivers of the same module have quite similar deviation point, which was expected after all, because always the two receivers of one module were tested simultaneously. It

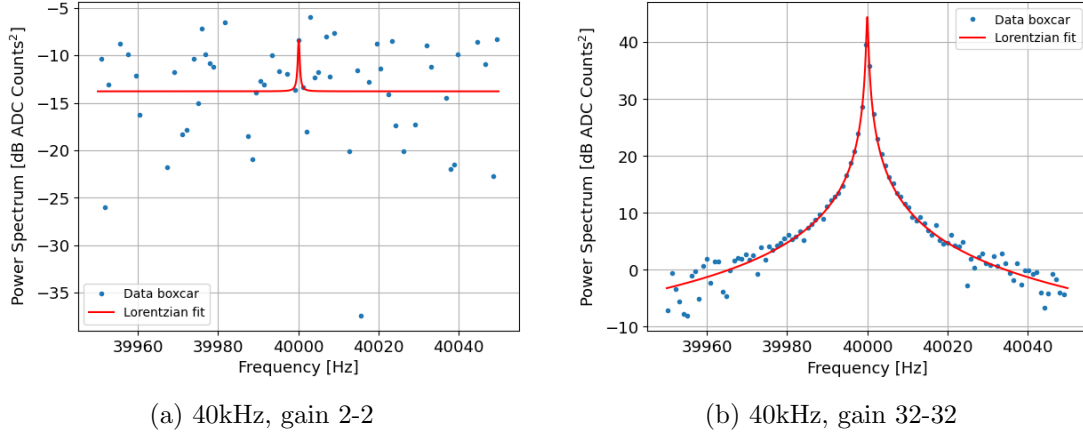


Figure 40: OM-4103 channel 2 periodograms with Lorentzian fits.

also looks like the frequency deviation over all gets higher for higher input frequencies, whereas gain mostly does not change the deviation. To get a better view on the distribution of frequency deviation from different input frequencies with fixed gain settings, I also plotted histograms with 100 bins between -1Hz and 1Hz deviation, shown in Figure 41. They indicate how often the deviations occur for each initial frequency.

In this histograms it gets clear that most of the peak frequencies have a way smaller deviation than 0.5Hz , with most counts somewhere between 0Hz and 0.25Hz . But you can also see that for 10kHz the deviation is smallest and with higher gains the deviation gets also higher. This is something to keep in mind when selecting the gain for further work with the modules. However, the deviation is small enough in any case that we can still speak of over all accurate frequency response of the receivers.

In summary, the Lorentzian fit on the boxcar-windowed periodograms of the measurements gets us great frequency responses for all measurements that have at least a small frequency peak in their power spectrum, with very small deviations from the input frequencies.

4.2.2 Frequency peak amplitude

As a last point of interest for the analysis, we can now have a look at the amplitudes of the periodogram peaks. These amplitudes can also be helpful to get the optimal gain settings for further use of the receivers. To get the amplitude of a frequency peak, I just used the amplitude parameter of the Lorentzian fit. As mentioned in subsection 3.3, the amplitude A_p of the fit I used is equal to A^2 , where A is the amplitude in the original sense. This means, that I have to take the square root of the A_p parameters I get from my fits, to get the physically relevant amplitude.

At first, I wanted to check whether there are dependencies of the amplitude on the frequency or gain over all receivers, so I took the mean value of the amplitude parameters of all receivers and plotted it first over all input frequencies and each gain setting separately and after that vice versa, with the standard deviation as errors. The two plots can be seen in Figure 42.

You can see immediately that both of this plots are very similar to the plots in Figure 21 for the peak-to-peak amplitude, which makes sense, as A is the amplitude of the

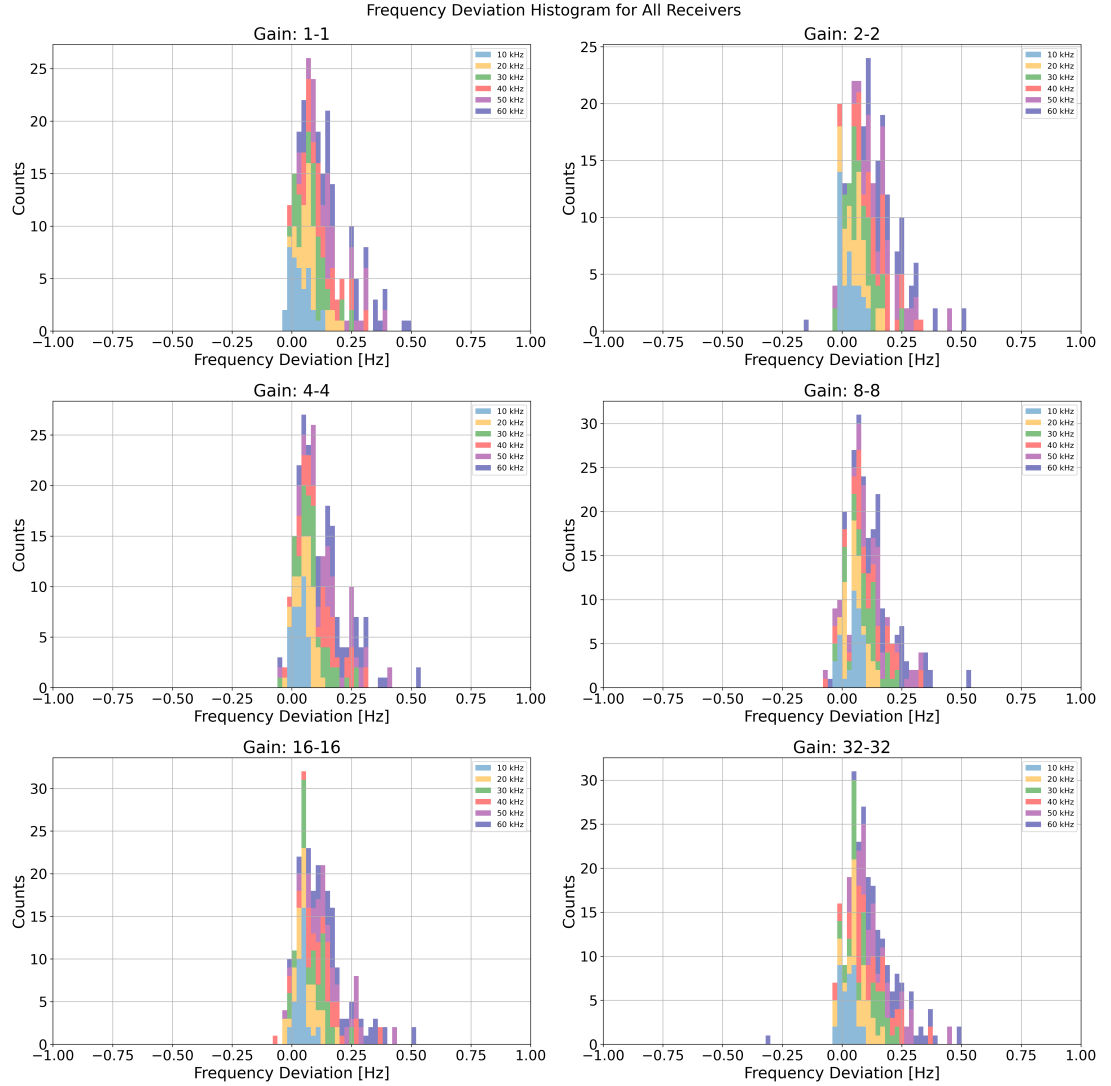
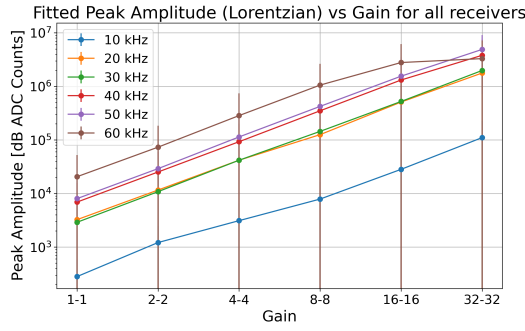


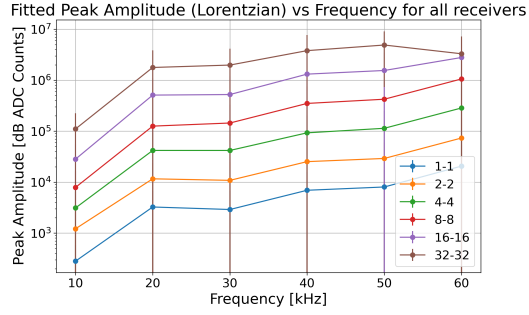
Figure 41: Histogram of frequency deviations with different input frequencies with 100 bins between -1Hz and 1Hz .

input signal. You can also again tell that the amplitude of the peaks rise with higher gain, which makes sense because the signal gets more amplified, but also with higher frequency. So the fitted peak amplitude has the same course as the other amplitude based parameters. Next, it is also of interest to have a look at the peak amplitudes for all receivers at all frequencies and gains, which is shown in Figure 43. The errors of this plot are the errors of the fit parameter gained by the square root of the respective covariance matrix parameter.

It is clearly visible that the value of the points overall increases with higher gain. You can also tell that the amplitudes of the peaks of CAL-0305 channel 1, OM-11 channel 2, OM-4035 channel 2 and OM-4103 channel 2, which had a A_p value above the lower bound of 10 ADC Counts², are much lower than all other amplitudes. In addition, this plot as well as the plots in Figure 42 shows clearly, that the peak amplitude gets way higher for higher gains, which indicates a better signal-to-noise ratio. For further use of



(a) Versus gain.



(b) Versus input frequency.

Figure 42: Mean amplitude value of all receivers for all input frequencies plotted versus gain (a) and for all gain settings plotted over the input frequency (b).

the receivers, I would not recommend using 10kHz signals, because the peak amplitude then is about one order of magnitude smaller than the next used frequency step of 20kHz, as you can tell from the plots of Figure 42a and Figure 43.

As final step of the analysis of the peak amplitude, we can now have a look at how many peak amplitude values have which magnitude for which gains using histograms sectioned in the different input frequencies. Those histograms are shown in Figure 44. It can be seen that lower gains have smaller amplitudes and that they often do not deviate that much. Gain 1-1 for example has many counts in one bin at very small amplitudes. With higher gains, the amplitudes get higher and each gain gets separated in more bins with lower counts until the last few bins are just the highest gains.

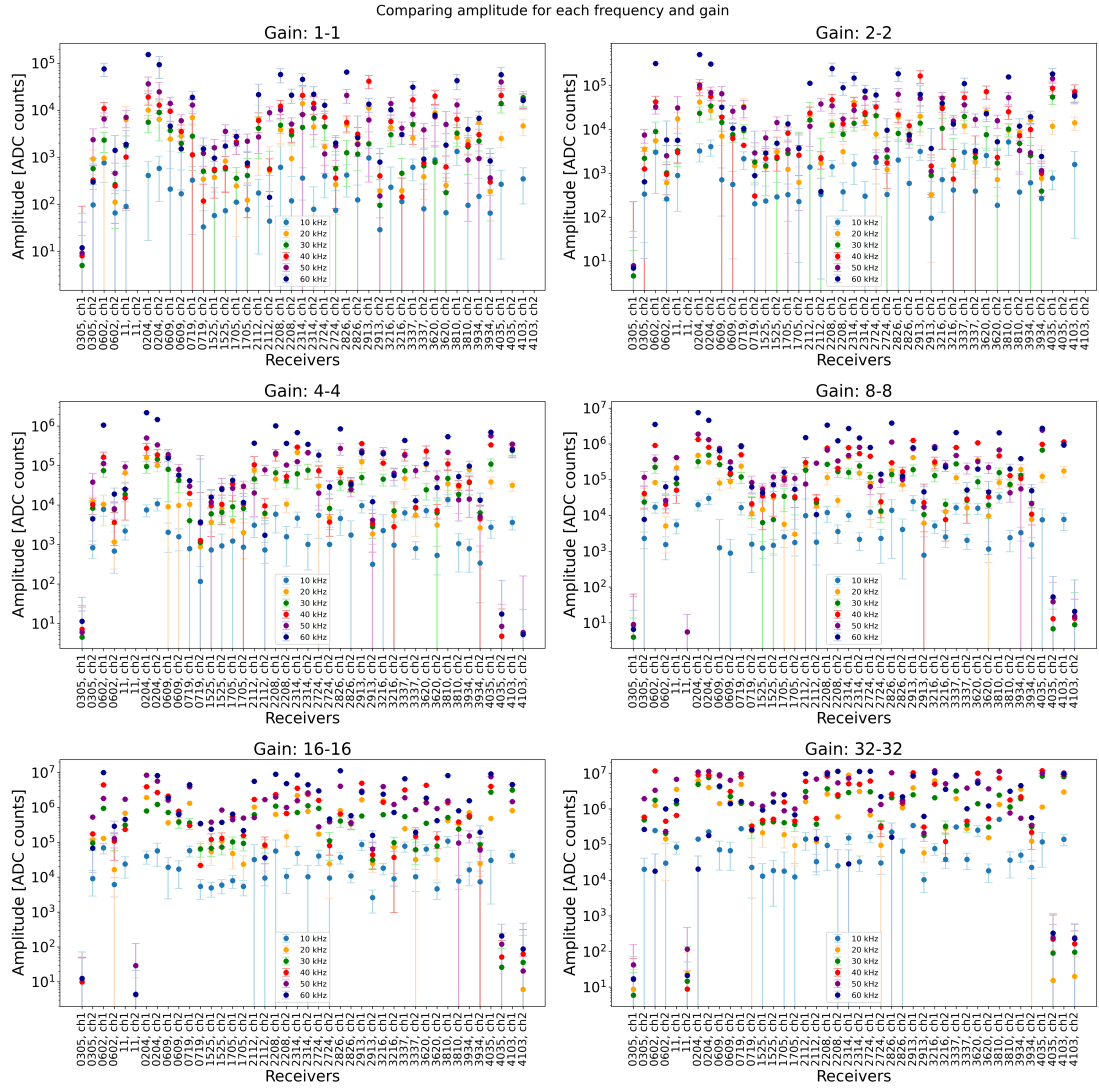


Figure 43: Amplitudes of the power spectrum peaks for all receivers, gain settings and initial frequencies.

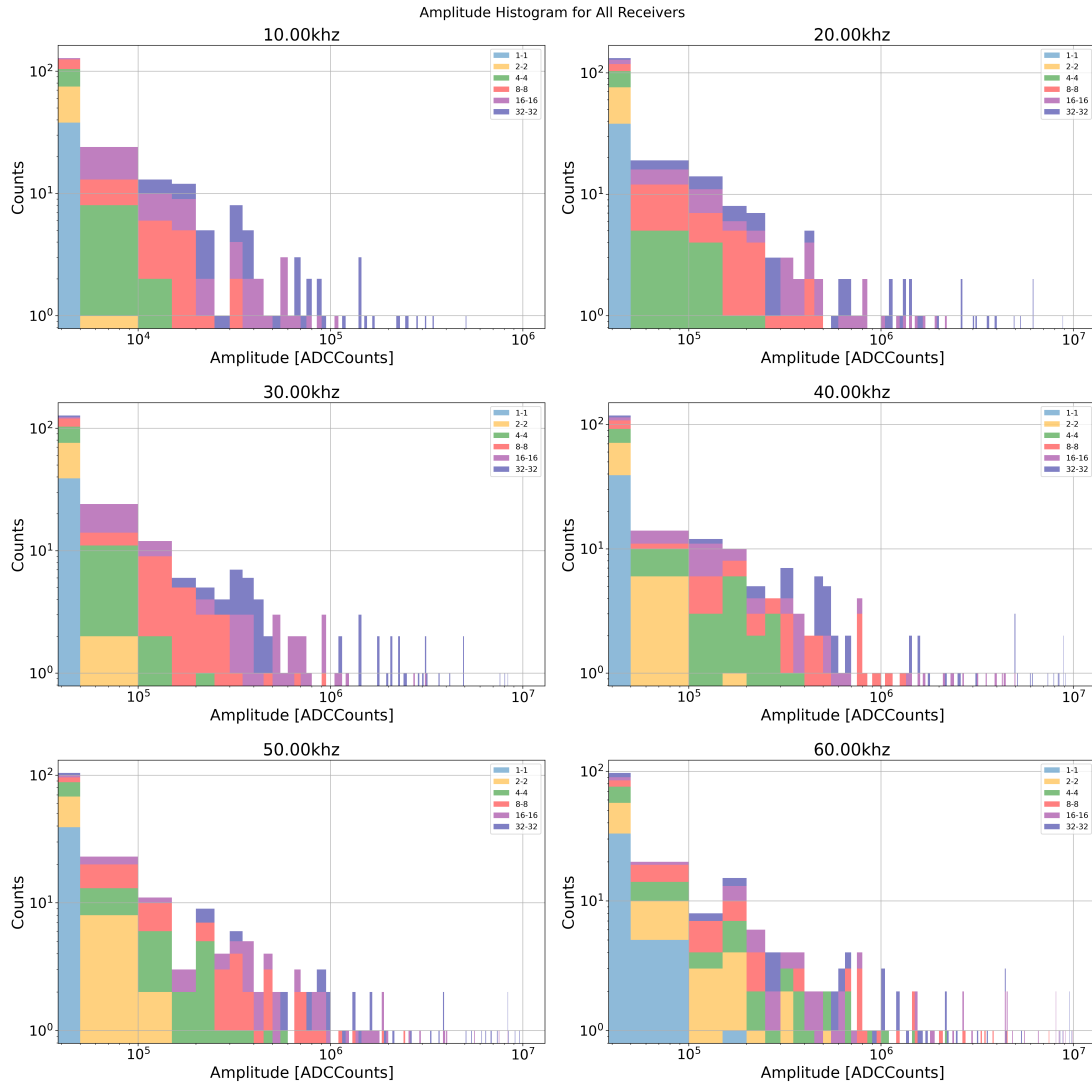


Figure 44: Histograms with 200 bins of peak amplitude counts as a function of gain sectioned in each input frequency.

5 Conclusion

This thesis presents the characterization of the acoustic sensors of P-ONE-1 based on laboratory acceptance data, which are crucial to track the position of the detector modules in the ocean. Those receivers are integrated in every hemisphere of the optical and calibration modules of P-ONE-1. The characterization consists of two analysis parts: the time-based and the frequency-based receiver properties of the piezo-acoustic receivers.

Using the MINT system as final acceptance test of the modules, the acoustic system was tested by sending out acoustic signals by an external buzzer coupled on the glass of each hemisphere and gaining the output signals from the piezo-acoustic receiver via an ADC. Data from the MINT acceptance tests were provided for analysis in this thesis. At the first part of the analysis, time-based receiver properties were characterized. For this, every output signal of the 36 measurements, that were performed for each of the 41 hemispheres, was examined based on their offset, standard deviation, peak-to-peak amplitude and RMS.

When considering the offset, expected to be 0 because of AC-coupling of the signals, one can clearly see that the offset deviates strongly from 0 for higher gains. The standard deviation and the peak-to-peak value have a pretty similar dependence of input frequency and gain setting, because both being values of amplitude. You can see both values rising with higher gains, as expected, because the gain amplifies the amplitudes, and also with higher input frequencies. The RMS has its highest values averaged at gain 4-4 or 8-8, dropping to its lowest values at 1-1 and 32-32, for all frequencies except 10kHz. This specific frequency has a RMS that rises continuously with gain, which could be a result of the high-pass filter with its roll-off frequency of 10kHz that gets slightly smaller with higher gains.

To analyze the frequency-based properties, this thesis presents different methods to do this and finds that the ideal option is using the power spectra of the measured signals in dB units with suited fits. These power spectra show, which frequency of the observed signal occurs with most power. I obtained these spectra by creating periodograms from the provided data.

The properties of interest to obtain from the power spectra are the peak frequency, that is equivalent with the frequency response of the receivers, and the amplitude of the peak. I tried to resolve the peak frequency by performing the periodogram of a signal with hann windowing for better signal-to-noise ratio and using Double Gaussian and Lorentzian fits on the peaks of the power spectrum. The second Gaussian peak worked for this instance as a way to fit the background. Both of the fits were able to obtain the frequency response of all input frequencies and with every gain setting using a specific test module with deviations under or around 0.25Hz.

In a similar way, the peak frequencies of the test module were determined using a Gaussian and the Lorentzian fit after removing the noise of the power spectrum, utilizing measurements that were performed without an input signal. The results were similar to the frequency responses with noise, but this step showed that the Lorentzian curve is the better alternative to fit the frequency peak because of a smaller χ^2 value over all. With hann windowing, however, empirical Gaussian and Lorentzian fits were used as an

attempt to describe and characterize the observed spectra.

Using boxcar windowing, the power spectrum is physically described by a Lorentzian curve. The frequency responses of the test module with boxcar windowing periodograms and a Lorentzian fit in dB units also agreed with the input frequencies with deviations under or around 0.25Hz. Looking at all receivers, the frequency responses for most of the measurements could be obtained. The deviation of the frequency response over all receivers is below or around 0.5Hz, which indicates, that the receivers can resolve the input frequencies.

As the last observed frequency-based property, the peak amplitudes of the power spectra, also obtained with the Lorentzian fit on the boxcar windowed periodogram, have the same course as the standard deviation and the peak-to-peak amplitude, as it is also an amplitude parameter, rising with higher gain and input frequency.

Even though most receivers could be characterized using these properties, three receivers failed to be characterized and singular measurements failed. The measurements of two receivers with certain gain and frequency settings showed no output signal. In addition, the acoustic hemisphere of one calibration module did not work, so this ADC channel should have had no signal. Nevertheless, the ADC output returned signals of this receiver, which can be explained by crosstalk. Ultimately, two receivers had no obtainable frequency peaks for low gains and small peaks for higher gains. So this receivers could not be characterized with as much precision as the others. Despite these few exceptions, most receivers could be characterized. The receivers operate reliably and can accurately resolve incoming frequency signals.

A Appendix A: Fit parameters

In the analysis, three different fit types were used: Gaussian fits (G), double Gaussian fits (DG) and Lorentzian fits (L). Depending on the type of fit, the windowing used for the power spectrum and the analysis step, the fit parameter bounds were adjusted accordingly. The frequency window width (FWW), in which the frequency peak of the power spectrum could be fitted, is listed in Table 2.

Fit types and analysis steps	FWW [Hz]
DG, spectrogram example (Figure 26)	± 3000
DG, periodogram example (Figure 27)	± 100
DG, first fit comparison (Figure 28)	± 40
L, first fit comparison (Figure 28)	± 100
DG, OM-3620 fit comparison (Figure 29, Figure 30, Figure 31)	± 10
L, OM-3620 fit comparison (Figure 29, Figure 30, Figure 31)	± 100
L, comparison without offset (Figure 33, Figure 34, Figure 35)	± 100
G, comparison without offset (Figure 33, Figure 34, Figure 35)	± 100
L, all peaks with boxcar windowing	± 1

Table 2: Frequency window width of the parameters that describe the frequency of the frequency peak of the power spectrum (μ , f_0). The window defines the range around the initial frequency of the respective frequency peak, in which the peak could be fitted. The Gaussian fit of Figure 26 was performed without fit bounds.

B Appendix B: Module plots

For each time-based property, module plots were created showing the respective property for each module separately. So offset, standard deviation, peak-to-peak amplitude and RMS can be viewed for each module individually.

Also, the frequency response plots showing the peak frequency plotted versus the input frequency and the frequency deviation for every gain setting, produced using the Lorentzian fit and the power spectrum with boxcar windowing, were also performed for each module separately.

All of these module plots can be viewed at

<https://git.ecap.work/ew98elyd/fpuerschel-bsc-2026.git>.

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Declaration of Originality

I, Fabian Pürschel, student registration number: 23319673, hereby confirm that I completed the submitted work independently and without the unauthorized assistance of third parties and without the use of undisclosed and, in particular, unauthorized aids. This work has not been previously submitted in its current form or in a similar form to any other examination authorities and has not been accepted as part of an examination by any other examination authority.

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