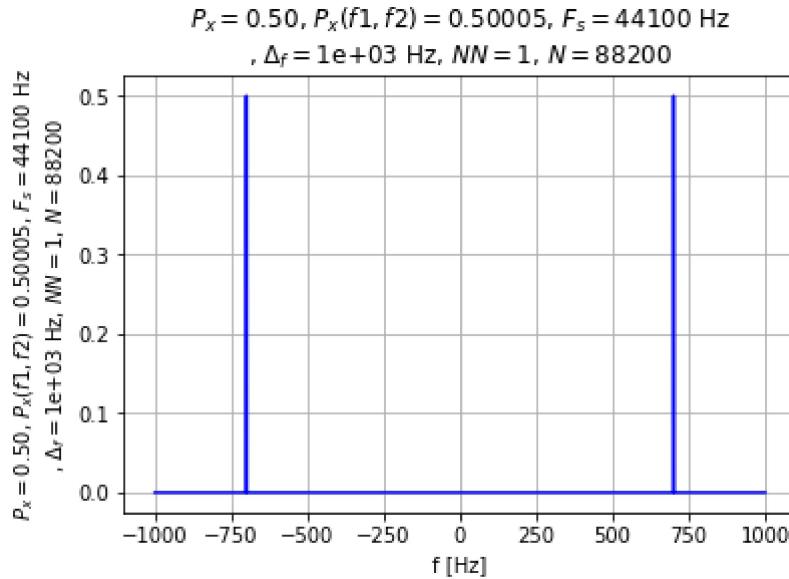


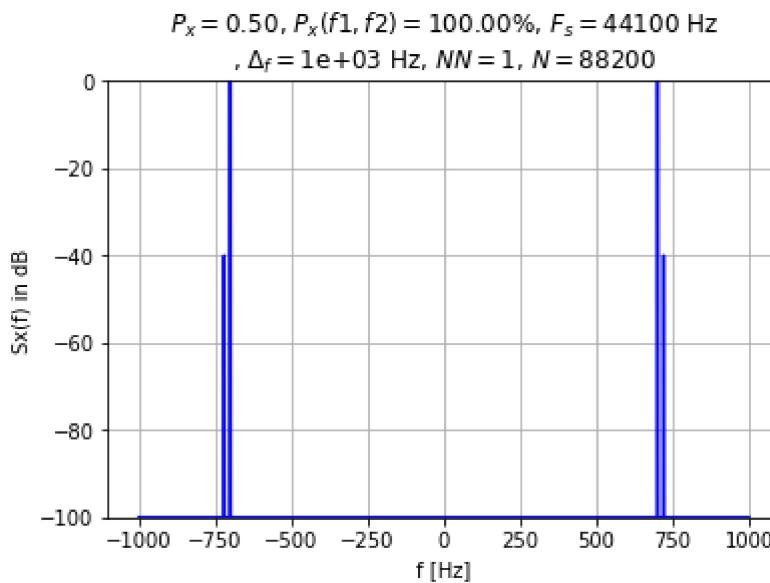
## Expt 1 (a)

In [2]: run Q1A



Both the sinusoids are not visible in this case. We enhance the code to display PSD in db so spectral lines of both waveforms are visible

In [2]: run Q1A

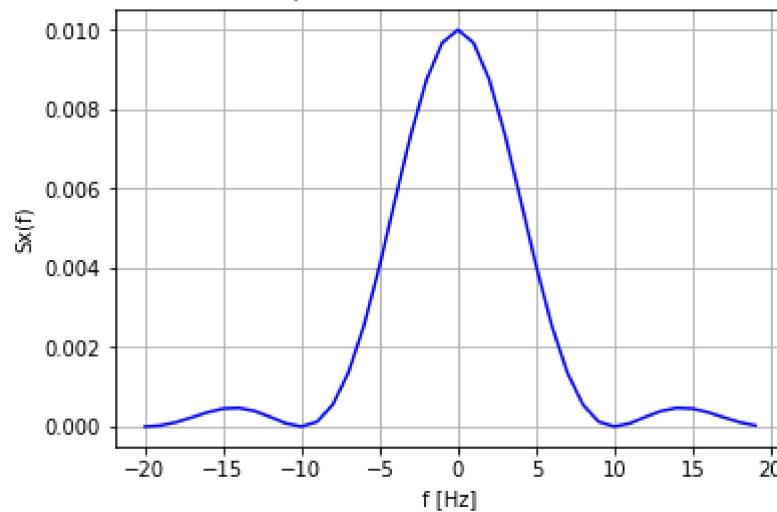


In the above figure both sinusoids are now visible

## Expt 1 (b)

In [2]: run Q1B

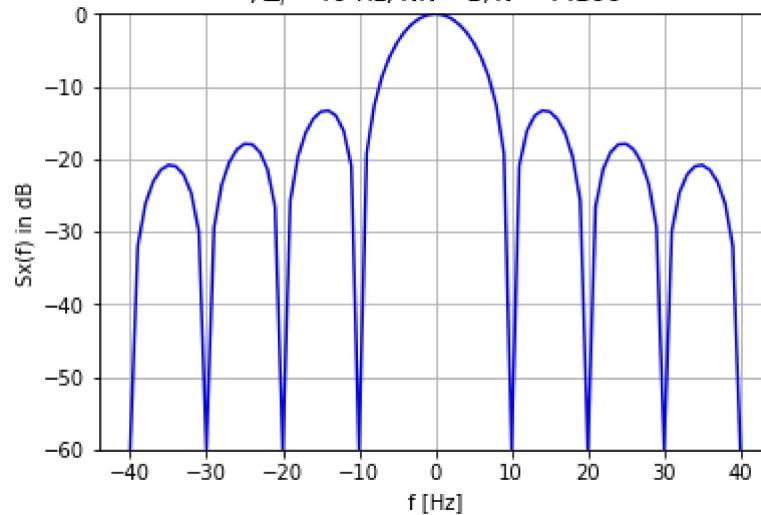
$P_x = 0.10, P_x(f_1, f_2) = 0.09499, F_s = 44100 \text{ Hz}$   
 $, \Delta_f = 19 \text{ Hz}, NN = 1, N = 44100$



The above diagram shows total power as well as power over a range of frequencies for a rectangular pulse of width 100 ms and amplitude 1. This graph uses a linear and absolute vertical axis and displays  $P_x(f_1, f_2)$  as an absolute value.

In [3]: run Q1B

$P_x = 0.10, P_x(f_1, f_2) = 97.47\%, F_s = 44100 \text{ Hz}$   
 $, \Delta_f = 40 \text{ Hz}, NN = 1, N = 44100$

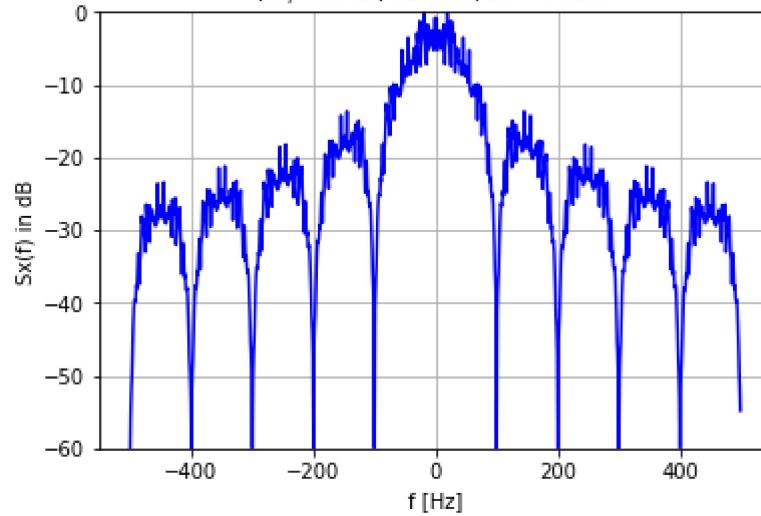


The second graph shows the  $S_x(f)$  of the same rectangular pulse normalized (i.e., maximum at 0 dB) and in dB and displays  $P_x(f_1, f_2)$  as a percentage of the total power  $P_x$

## Expt 1 (c)

In [8]: run Q1C

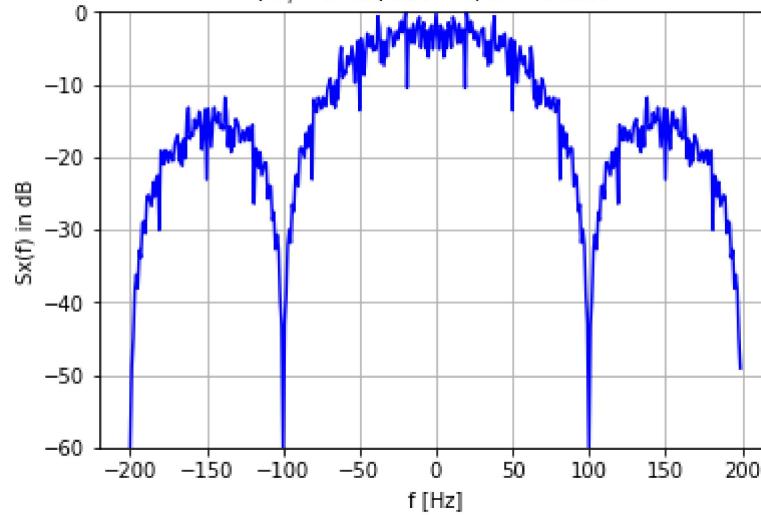
$P_x = 1.00, P_x(f_1, f_2) = 98.11\%, F_s = 44100 \text{ Hz}$   
 $, \Delta_f = 1 \text{ Hz}, NN = 5, N = 44100$



PSD of the rectangular PAM signal over a frequency range of -500, 500. It is equal to 98.11% of the total power.

In [9]: run Q1C

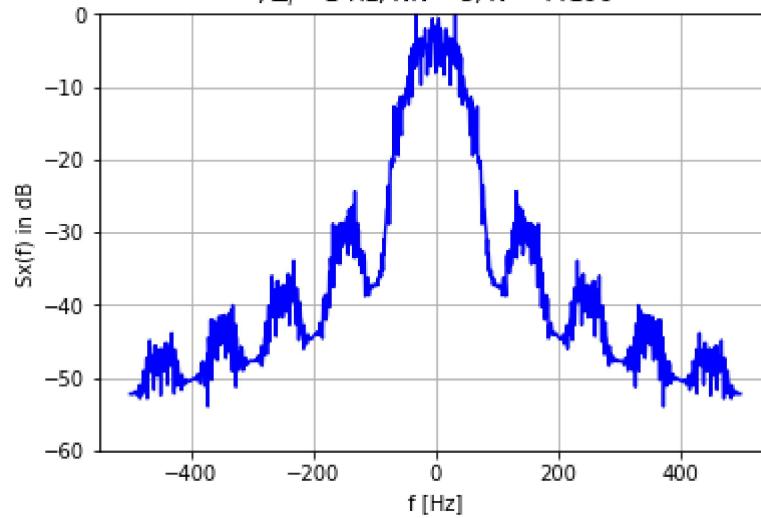
$P_x = 1.00, P_x(f_1, f_2) = 94.72\%, F_s = 44100 \text{ Hz}$   
 $, \Delta_f = 1 \text{ Hz}, NN = 5, N = 44100$



PSD of the rectangular PAM signal over a frequency range of -2Fb, 2Fb. It is equal to 94.72% of the total power.

In [10]: run Q1C

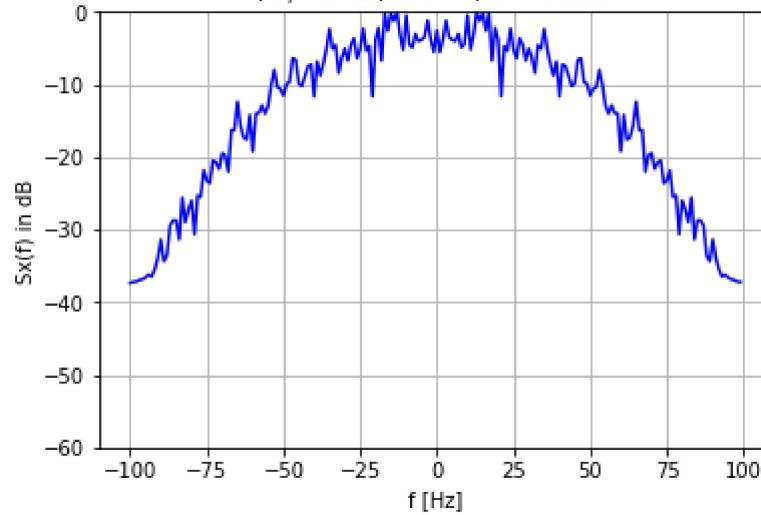
$P_x = 0.65, P_x(f_1, f_2) = 99.98\%, F_s = 44100 \text{ Hz}$   
 $, \Delta_f = 1 \text{ Hz}, NN = 5, N = 44100$



PSD of the triangular PAM signal over a frequency range of -500, 500. It is equal to 99.98% of the total power.

In [11]: run Q1C

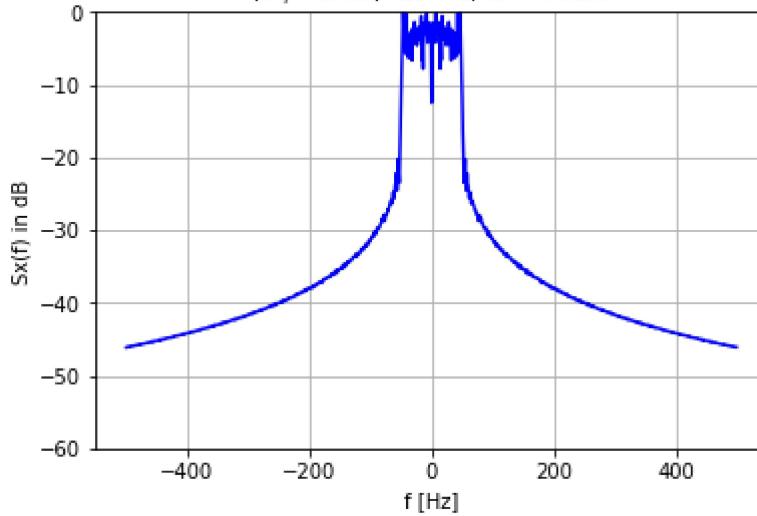
$P_x = 0.66, P_x(f_1, f_2) = 99.65\%, F_s = 44100 \text{ Hz}$   
 $, \Delta_f = 1 \text{ Hz}, NN = 5, N = 44100$



PSD of the triangular PAM signal over a frequency range of -Fb, Fb. It is equal to 99.65% of the total power.

In [12]: run Q1C

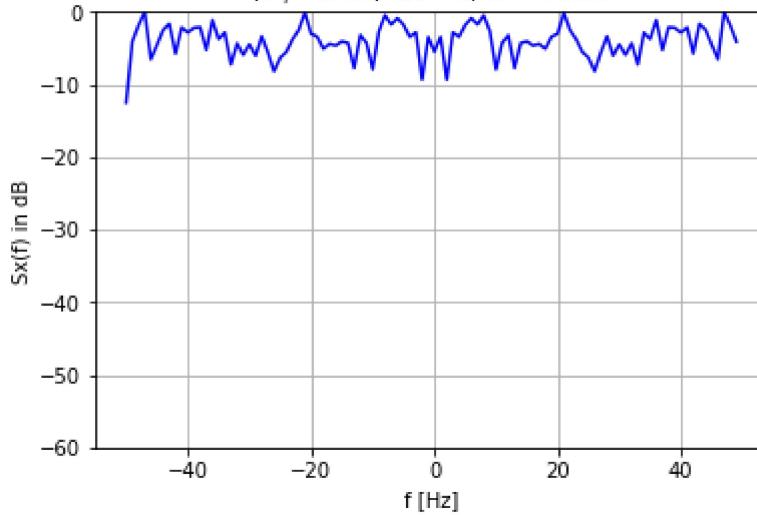
$P_x = 1.00, P_x(f_1, f_2) = 99.95\%, F_s = 44100 \text{ Hz}$   
 $, \Delta_f = 1 \text{ Hz}, NN = 5, N = 44100$



PSD of the sinc PAM signal over a frequency range of -500, 500. It is equal to 99.9% of the total power.

In [13]: run Q1C

$P_x = 1.00, P_x(f_1, f_2) = 99.14\%, F_s = 44100 \text{ Hz}$   
 $, \Delta_f = 1 \text{ Hz}, NN = 5, N = 44100$



PSD of the sinc PAM signal over a frequency range of -50, 50. It is equal to 99.14% of the total power.

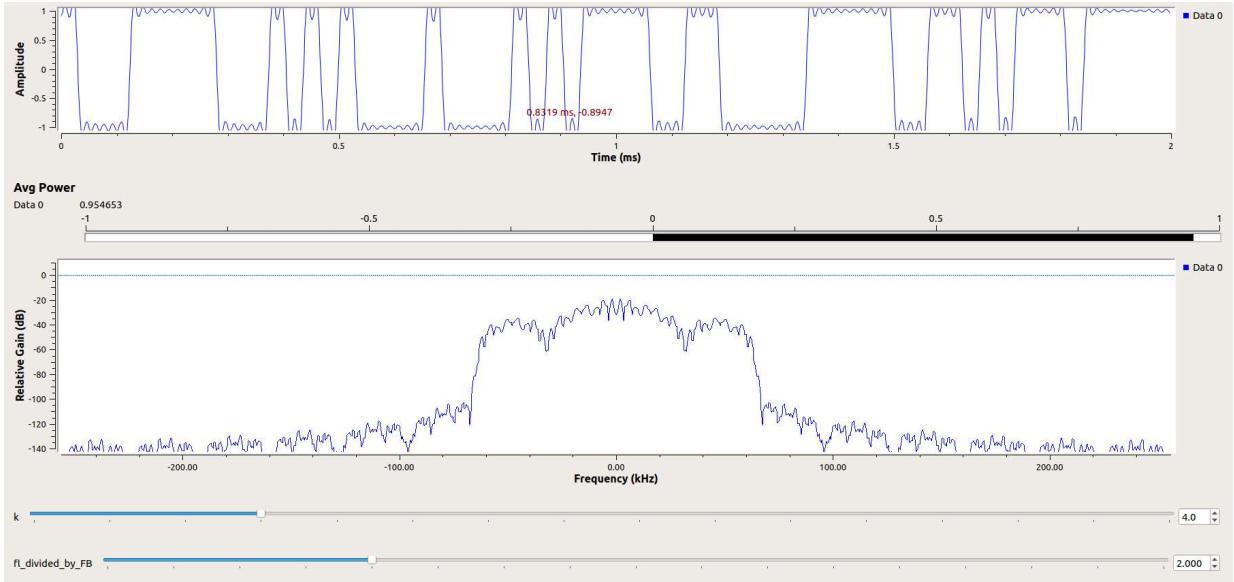
Thus for the rectangular, sinc and triangular signals we find that most of the power is contained within the corresponding bandwidth of  $2F_b, F_b/2, F_b$

## Expt 1(d)

PAM signal based on a rectangular pulse  $p(t)$  after low pass filtering at  $F_l = 2F_b$ . We observe that 95% of the total average power is contained in the bandwidth of  $F_b$

In [5]: `from IPython.display import Image  
Image(filename='capture.png')`

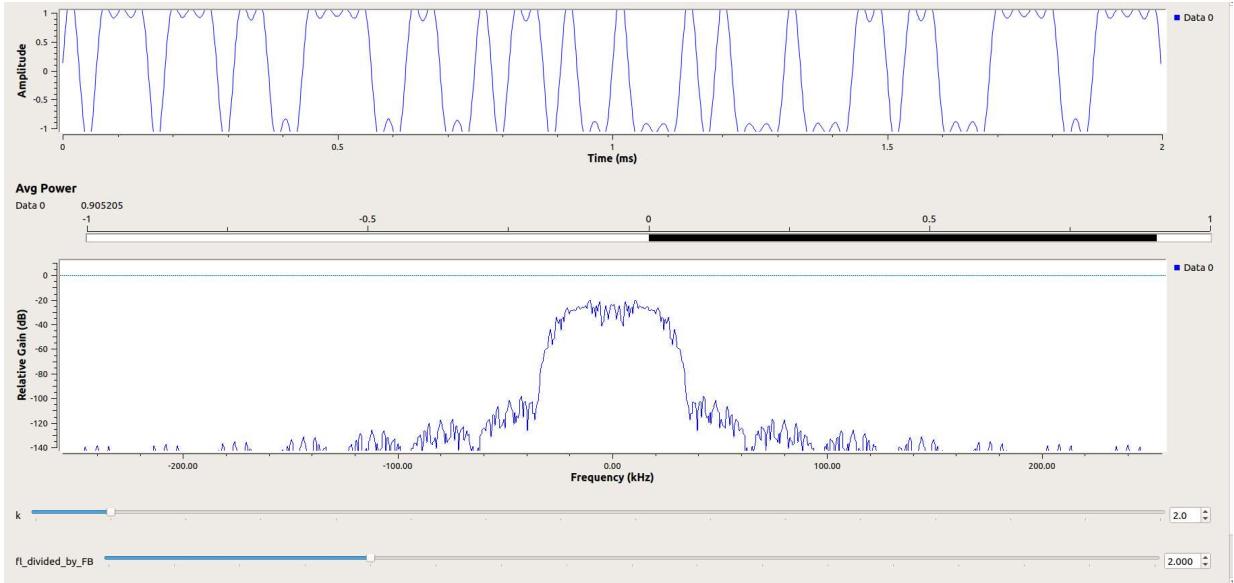
Out[5]:



PAM signal based on a triangular pulse  $p(t)$  after low pass filtering at  $F_l = F_b$ . The total power contained within the bandwidth of  $F_b$  is ~ 90%

In [6]: `from IPython.display import Image  
Image(filename='capture.png')`

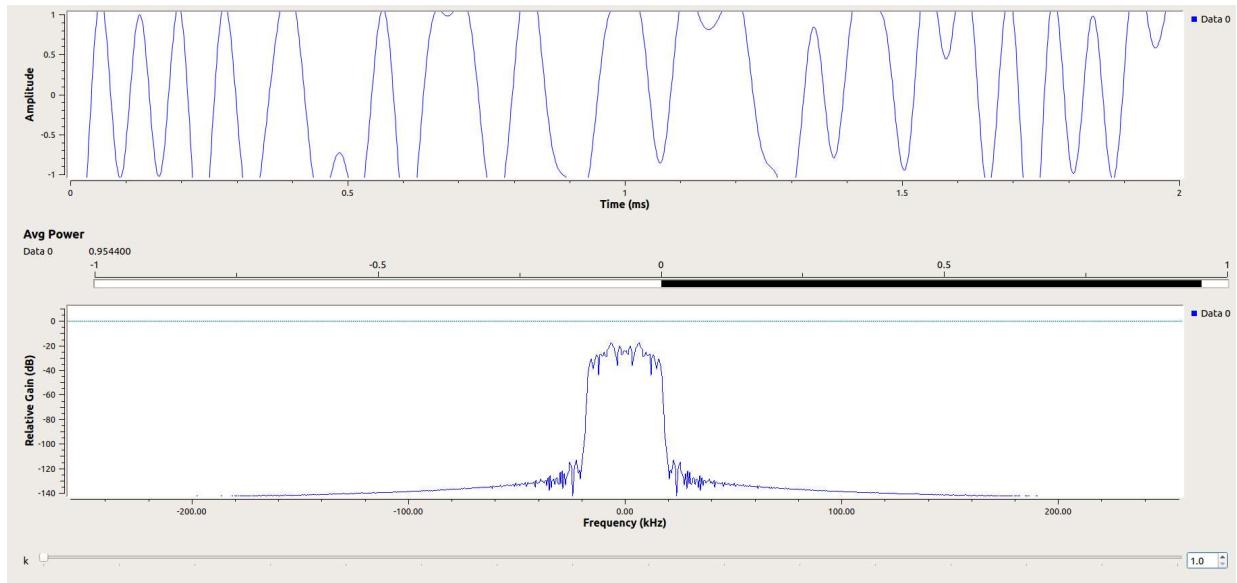
Out[6]:



PAM signal based on a sinc pulse after low pass filtering at  $F_l = F_b/2$ . ~ 95% of the total power is contained in this bandwidth

In [3]: `from IPython.display import Image  
Image(filename='capture.png')`

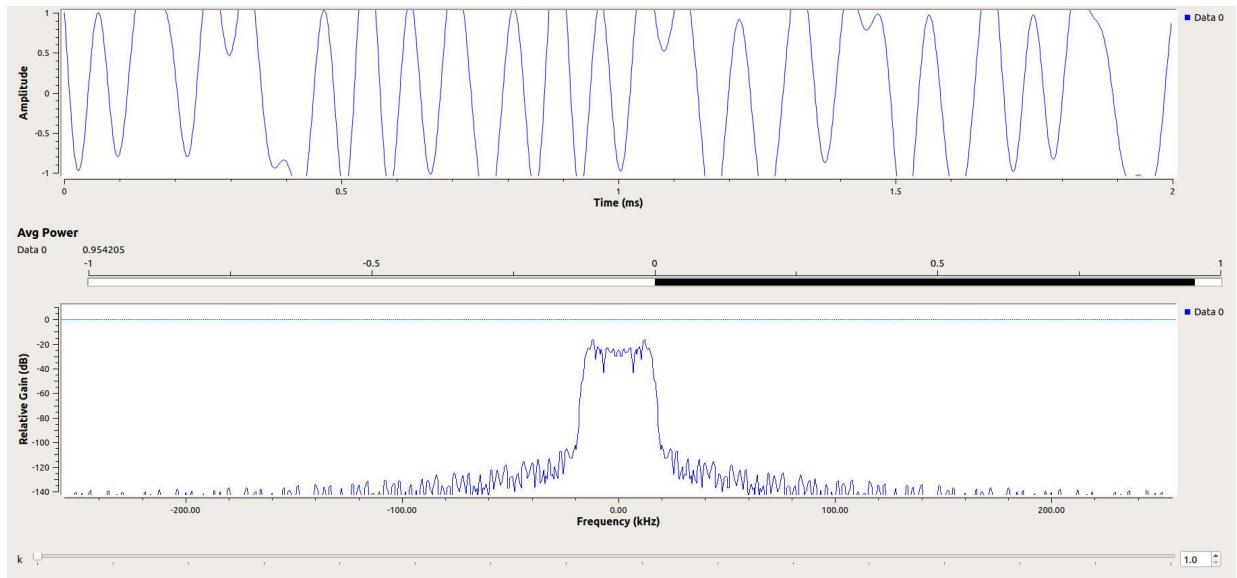
Out[3]:



PAM signal based on a RCf pulse after low pass filtering at  $F_l = F_b/2$ . The total power contained in this bandwidth is also 95%

In [4]: `from IPython.display import Image  
Image(filename='capture.png')`

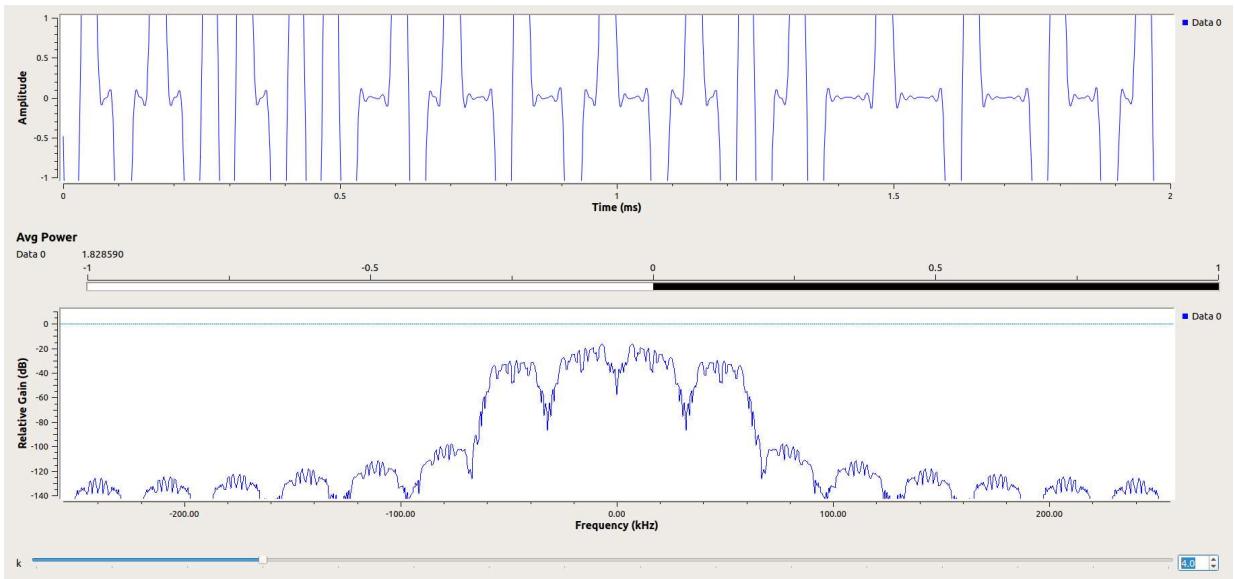
Out[4]:



PAM signal based on a manchester pulse after low pass filtering at  $F_l = 2F_b$  similar to rectangular signal, however We observe that the total average power is more than 100% which shouldnt be the case. But it can be justified by making a note of the fact that the amplitude is more than one in this case. This is causing the power to be more than 100%

In [6]: `from IPython.display import Image  
Image(filename='capture.png')`

Out[6]:

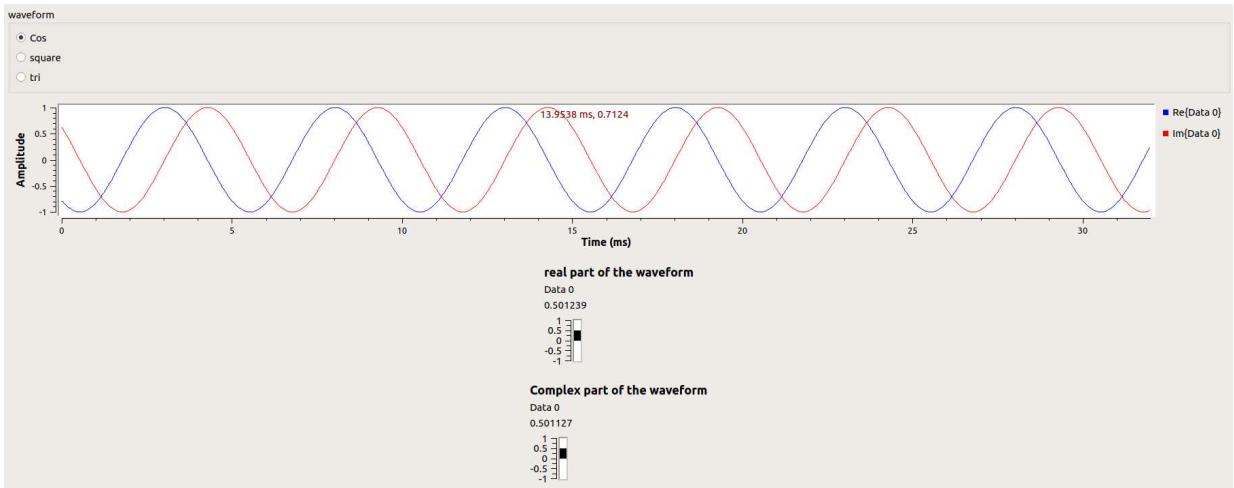


## Expt 1(e)

Power for Complex Valued Cosine Waveform

In [10]: `from IPython.display import Image  
Image(filename='capture.png')`

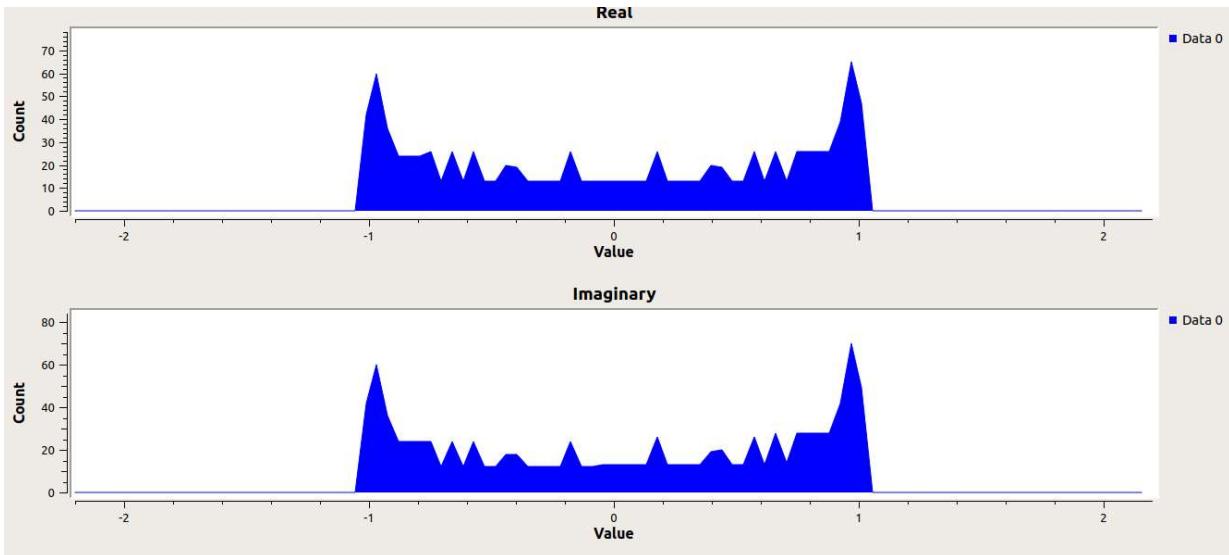
Out[10]:



Average power of the complex = Average part of the real part  $\approx 50\% = 1/2$  (Total average of the waveform)  
 Total average power of the complex valued waveform = Total average power for the real valued waveform  $\approx 100\%$

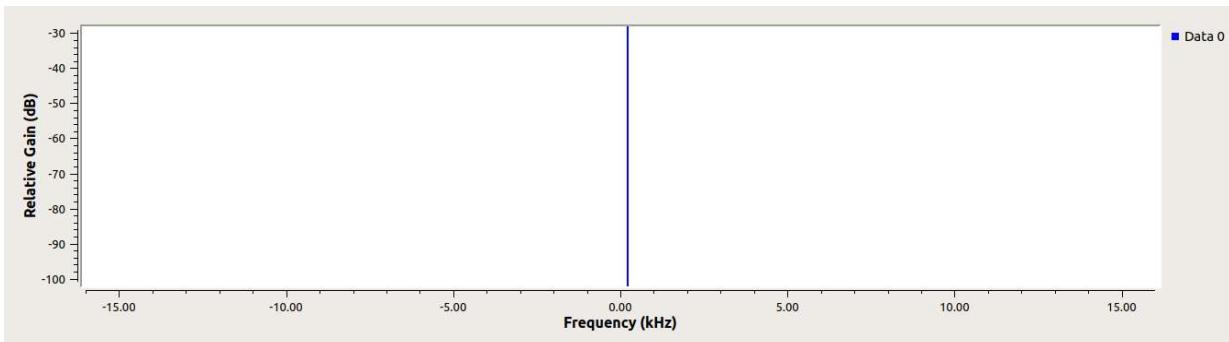
In [11]: `from IPython.display import Image  
Image(filename='capture.png')`

Out[11]:



In [12]: `from IPython.display import Image  
Image(filename='capture.png')`

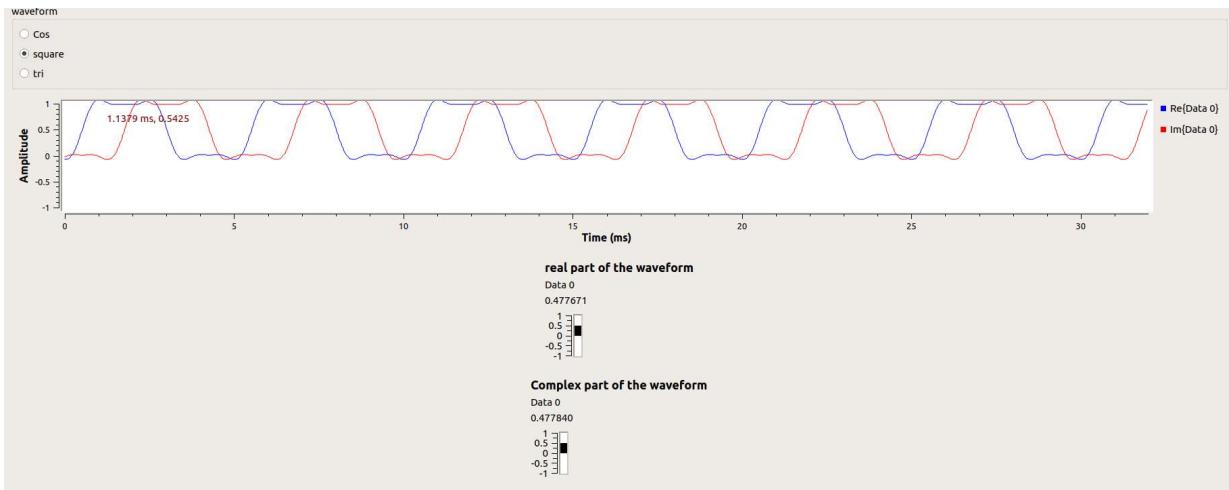
Out[12]:



### Power for complex valued Square Waveform

In [13]: `from IPython.display import Image  
Image(filename='capture.png')`

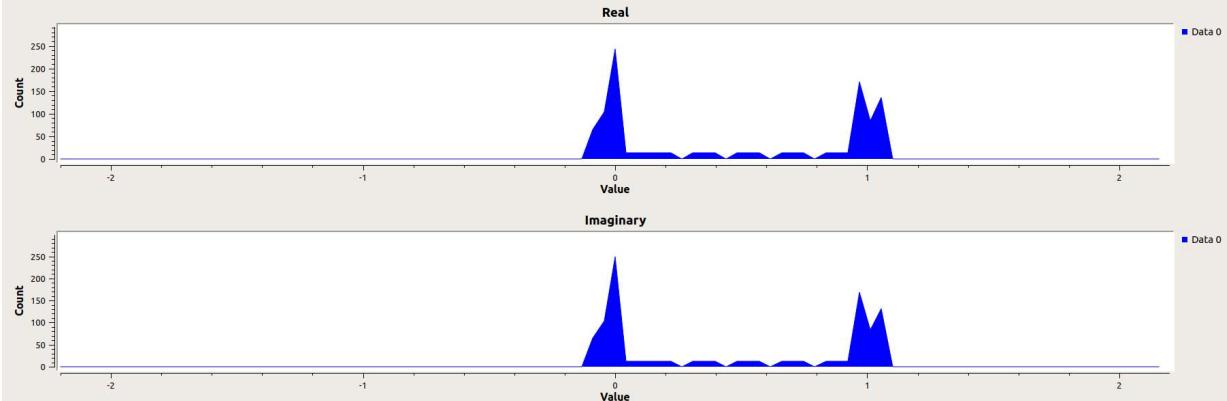
Out[13]:



Average power of the complex = Average part of the real part  $\approx 48\% = 1/2$  (Total average of the waveform)  
 Total average power of the complex valued waveform = Total average power for the real valued waveform  $\approx 97\%$

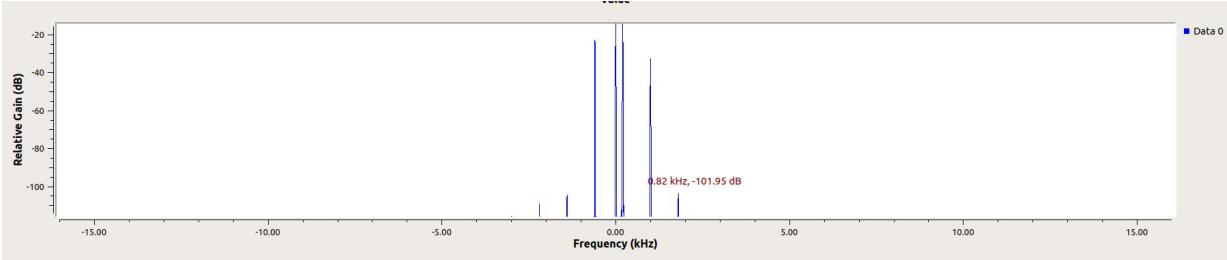
In [14]: `from IPython.display import Image  
Image(filename='capture.png')`

Out[14]:



In [15]: `from IPython.display import Image  
Image(filename='capture.png')`

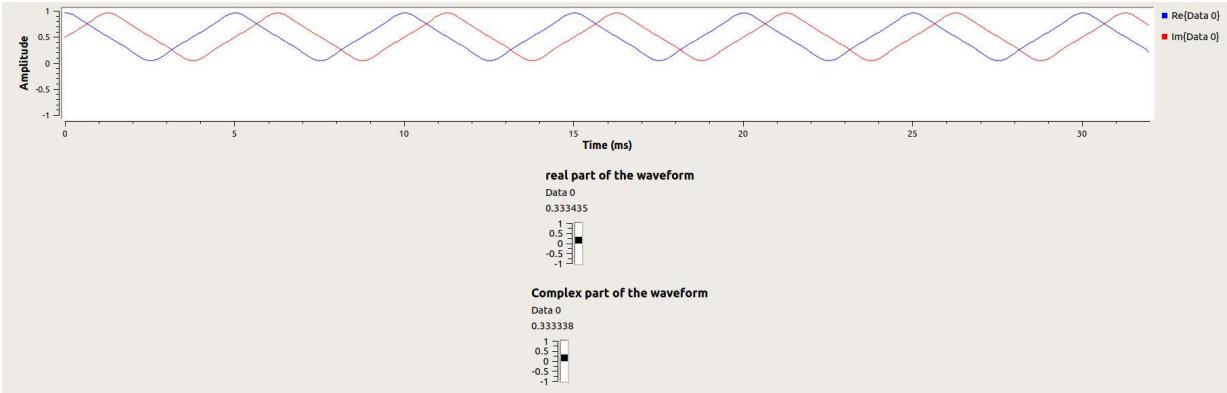
Out[15]:



Power for complex valued Triangular waveform

In [16]: `from IPython.display import Image  
Image(filename='capture.png')`

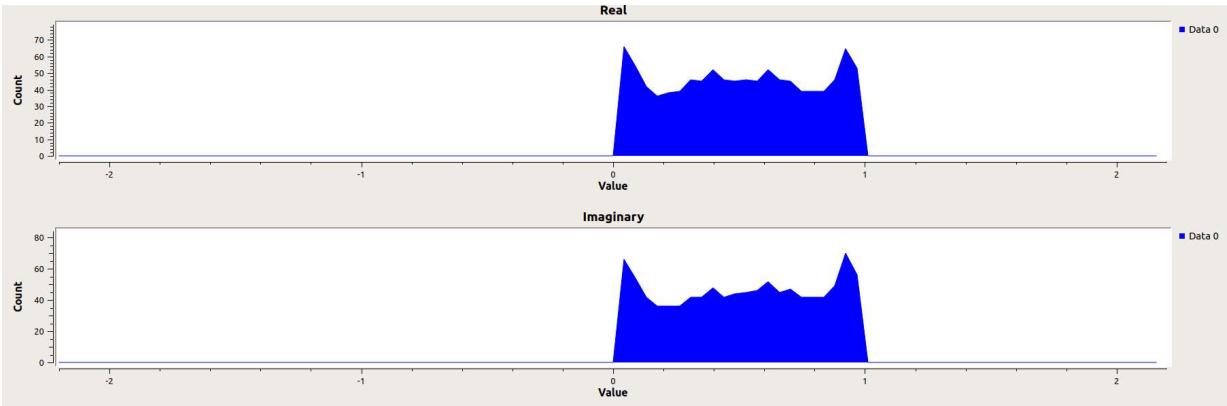
Out[16]:



Average power of the complex = Average part of the real part  $\approx 33\% = 1/2$  (Total average of the waveform)  
 Total average power of the complex valued waveform = 67% is not equal to Total average power for the real valued waveform  $\approx 99\%$ . The difference can be explained by looking at the triangular wave. We observe that the Peak to Peak amplitude is only 0.5 instead of 1.

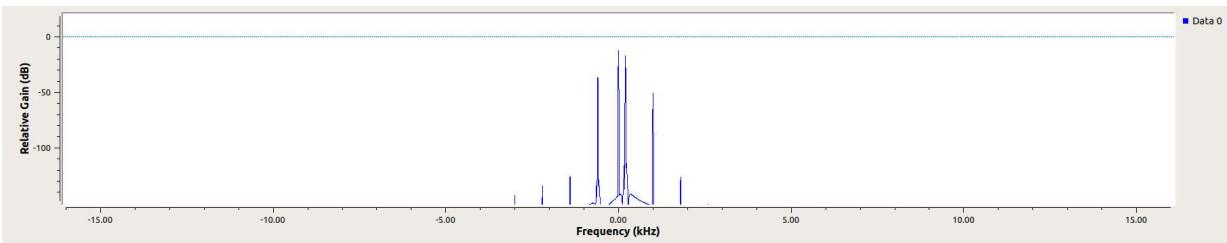
In [17]: `from IPython.display import Image  
Image(filename='capture.png')`

Out[17]:



In [18]: `from IPython.display import Image  
Image(filename='capture.png')`

Out[18]:

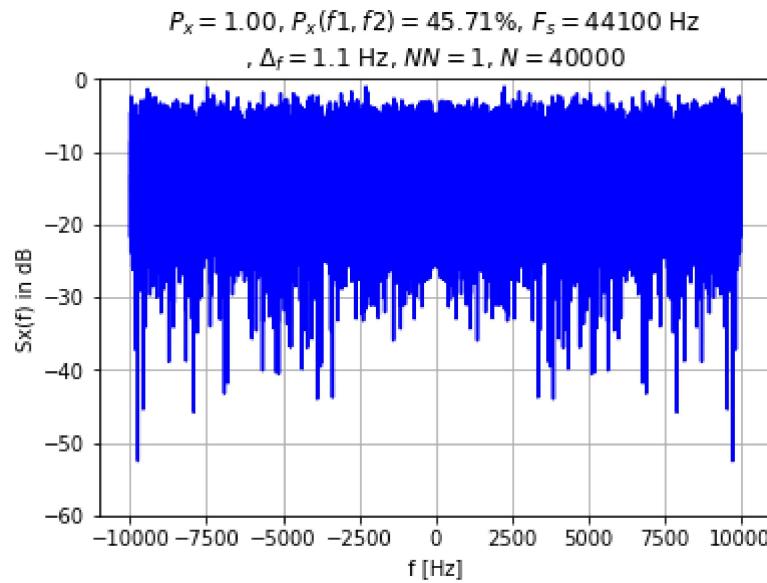


For all three complex valued waveform we observe that the power contained in the real part is the same as the imaginary part. Both are approximately half of the total average power of the signals.

The total average power of the complex valued waveform is nearly the same and comparable with the real valued waveform. We compare with the real valued waveform Power values form Q1(a), (b),(c)

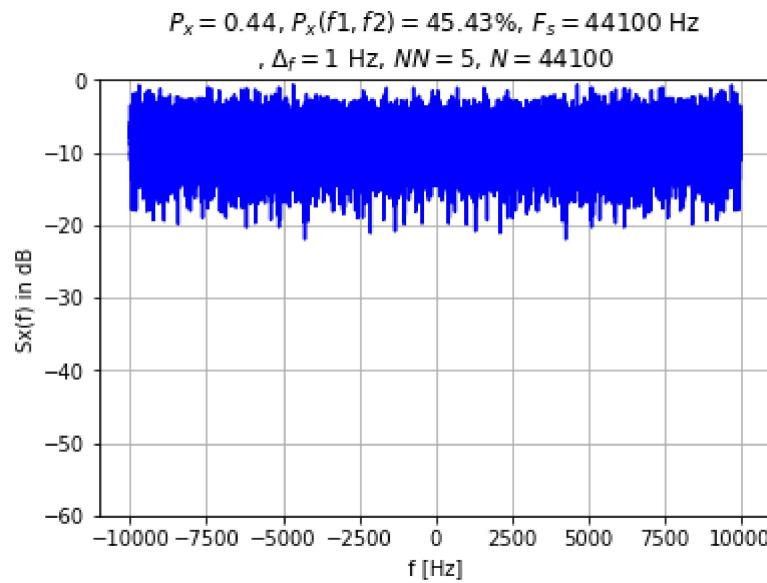
## Expt 2(a)

In [3]: run Q2A



The above plot is the PSD of white gaussian noise

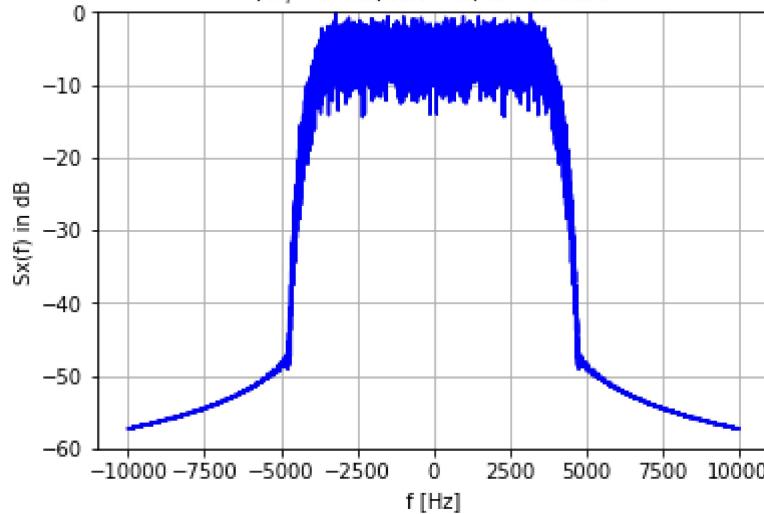
In [2]: run Q2A



The above plot is the PSD for full bandwidth Gaussian noise

In [3]: run Q2A

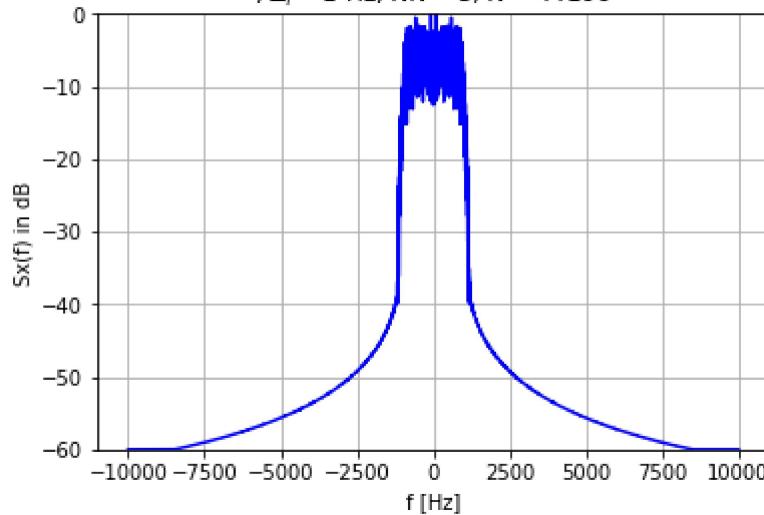
$P_x = 0.95, P_x(f_1, f_2) = 100.00\%, F_s = 44100 \text{ Hz}$   
 $, \Delta_f = 1 \text{ Hz}, NN = 5, N = 44100$



The above plot is the PSD of bandlimited Gaussian noise with  $f_L = 4000 \text{ Hz}$

In [4]: run Q2A

$P_x = 0.94, P_x(f_1, f_2) = 100.00\%, F_s = 44100 \text{ Hz}$   
 $, \Delta_f = 1 \text{ Hz}, NN = 5, N = 44100$



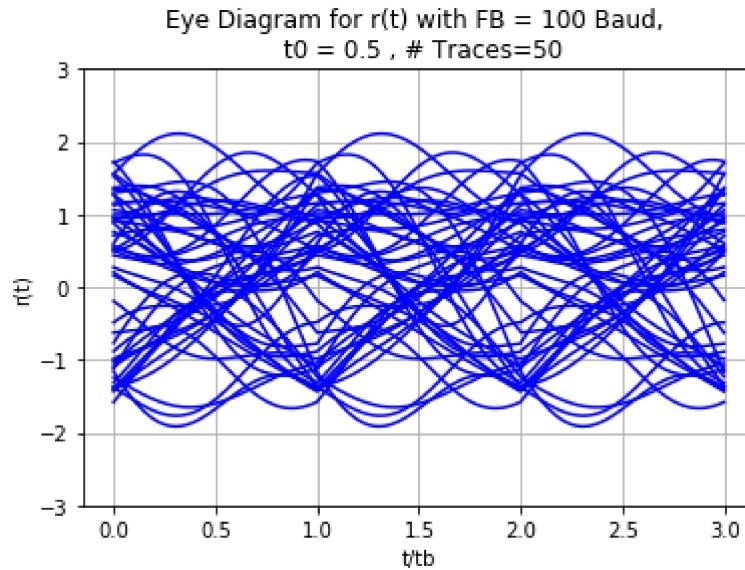
The above plot is the PSD of bandlimited Gaussian noise with  $f_L = 1000 \text{ Hz}$

The wav file containing the full bandwidth noise signal had the highest pitched white noise. The bandlimited signal with  $f_L = 4000 \text{ Hz}$  was slightly lower pitched than that and the one with  $f_L = 1000 \text{ Hz}$  had the lowest pitched white noise.

## Expt 2(b)

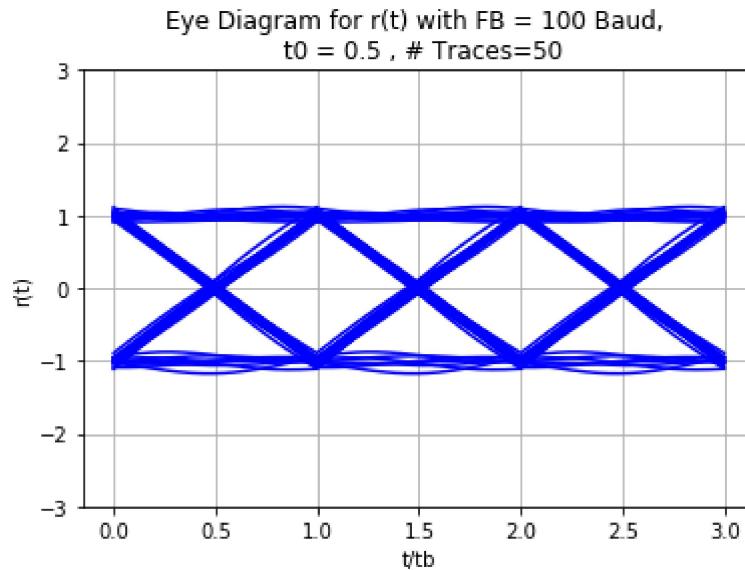
Generated a random polar binary PAM signal  $s(t)$  of length 2 sec with triangular  $p(t)$ . Used FB = 100 and Fs = 44100. Then generated bandlimited Gaussian noise  $n(t)$  with cutoff frequency  $f_L$  = FB (the rule of thumb bandwidth for PAM with triangular  $p(t)$ ). Used the showeye function to plot the eye diagram of  $r(t)$ , where  $r(t) = s(t) + An(t)$  be the received PAM signal.

In [11]: run Q2B



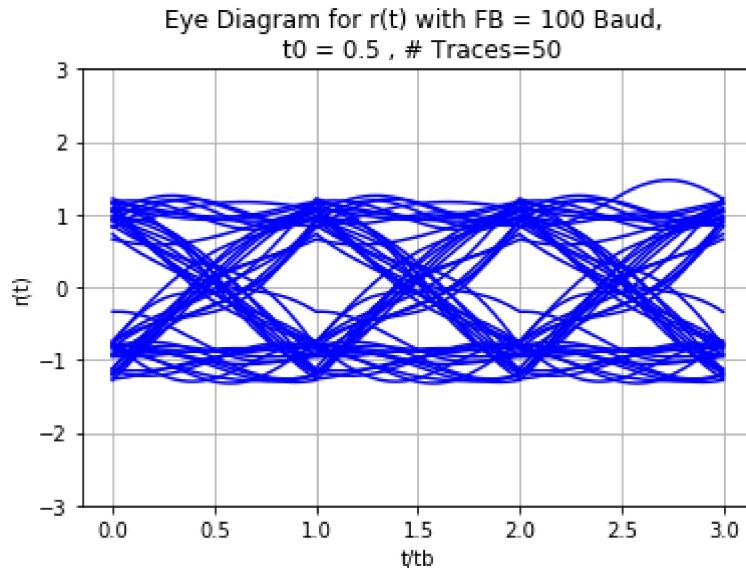
This eye diagram is for  $A = 0.5$

In [12]: run Q2B



This eye diagram is for  $A = 0.05$

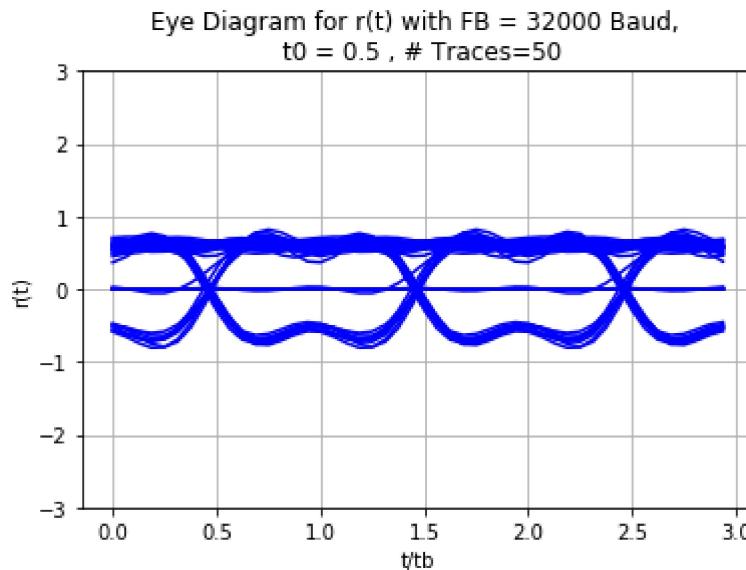
In [20]: run Q2B



The first two eye diagrams are examples of respectively 100% and 0% closure. The third eye diagram is somewhere between the two thus we find that 50% closure happens for  $A = 0.185$

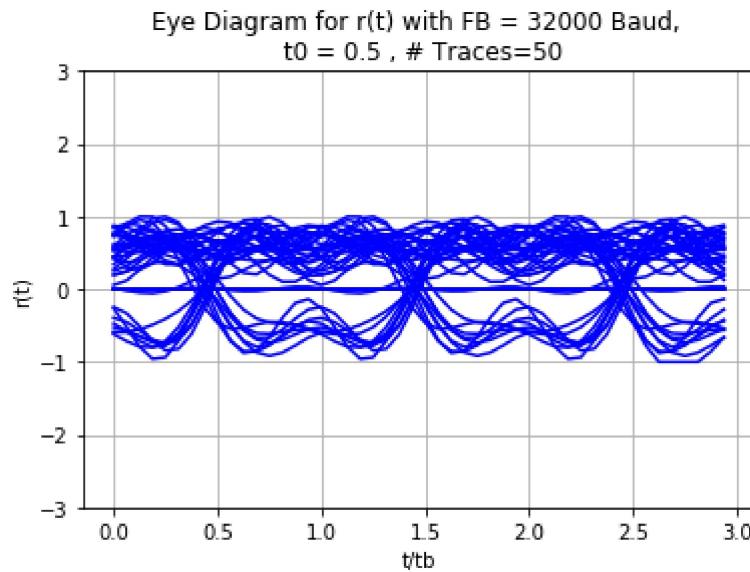
## Expt 2 (c)

In [3]: run Q2C



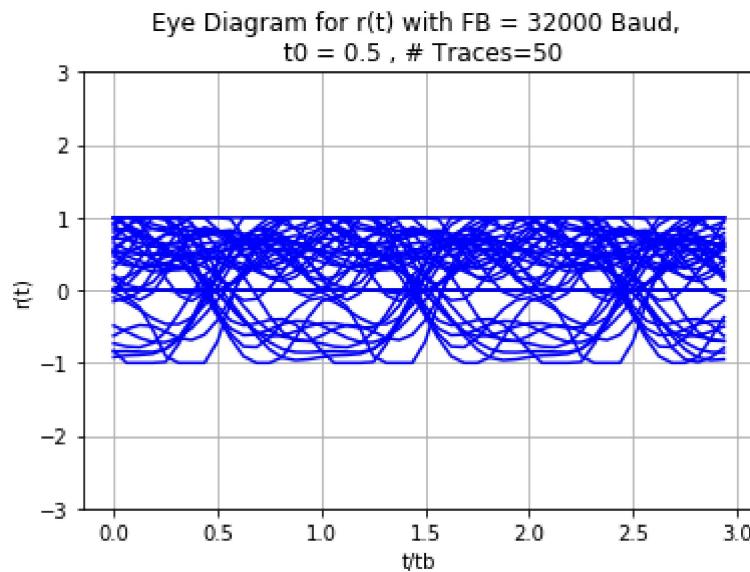
The above eye diagram is for a rectangular PAM with bandwidth (both noise and PAM signal)  $2FB$  and SNR of 20.

In [4]: run Q2C



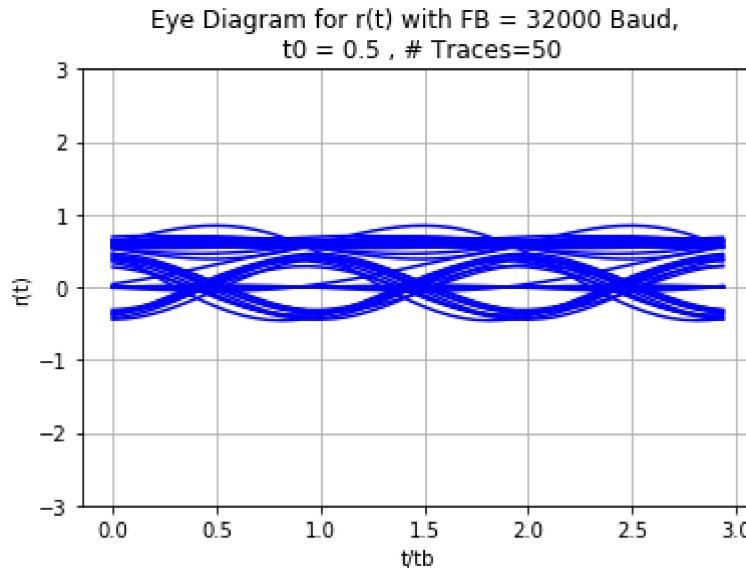
The above eye diagram is for a rectangular PAM with bandwidth (both noise and PAM signal) 2FB and SNR of 10

In [5]: run Q2C



The above eye diagram is for a rectangular PAM with bandwidth (both noise and PAM signal) 2FB and SNR of 5

In [7]: run Q2C



The above eye diagram is for a rectangular PAM with bandwidth (both noise and PAM signal)  $FB/2$  and SNR of 20. This most closely resembles the eye diagram of the rectangular PAM with bandwidth =  $2F_b$  and SNR of 10

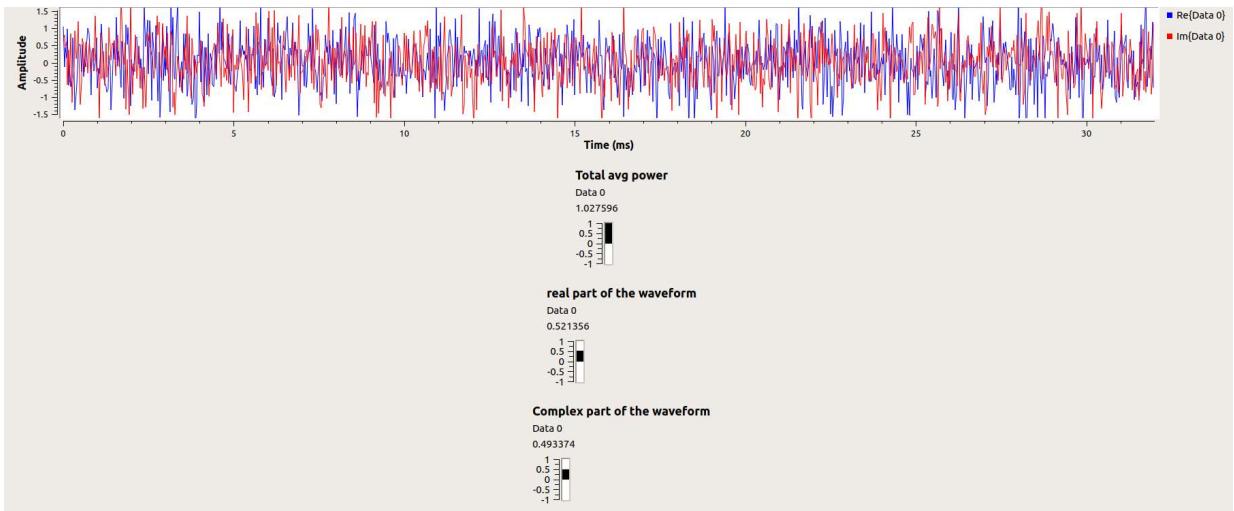
The PAM signal with SNR = 20 db is the one that's the least closed. The closure of the eye diagram keeps increasing as the SNR decreases Which makes sense analytically since the noise added to the signal is increasing as the SNR decreases.

## Expt 2(d)

Power of a complex valued gaussian noise in GRC with  $A = 1$ ,  $F_l = 16000\text{Hz}$ . The theoretical shape for the amplitude histogram should be a gaussian distribution

In [22]: `from IPython.display import Image  
Image(filename='capture.png')`

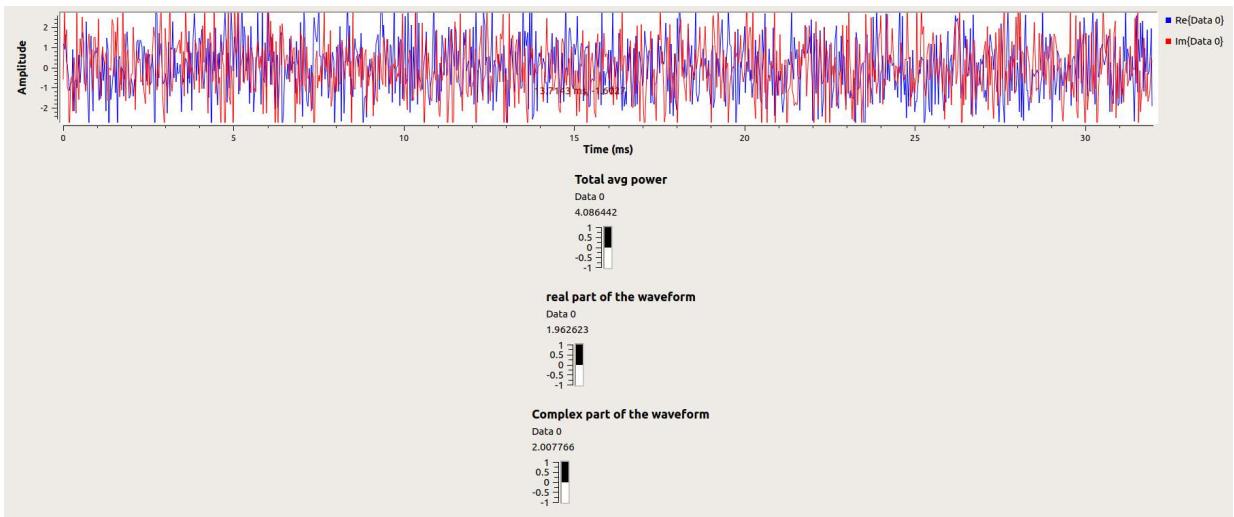
Out[22]:



We observe that the power of the real part is equal to the complex part of the waveform. Both of which are approximately = 50% which is half of the total average power = 100%

In [23]: `from IPython.display import Image  
Image(filename='capture.png')`

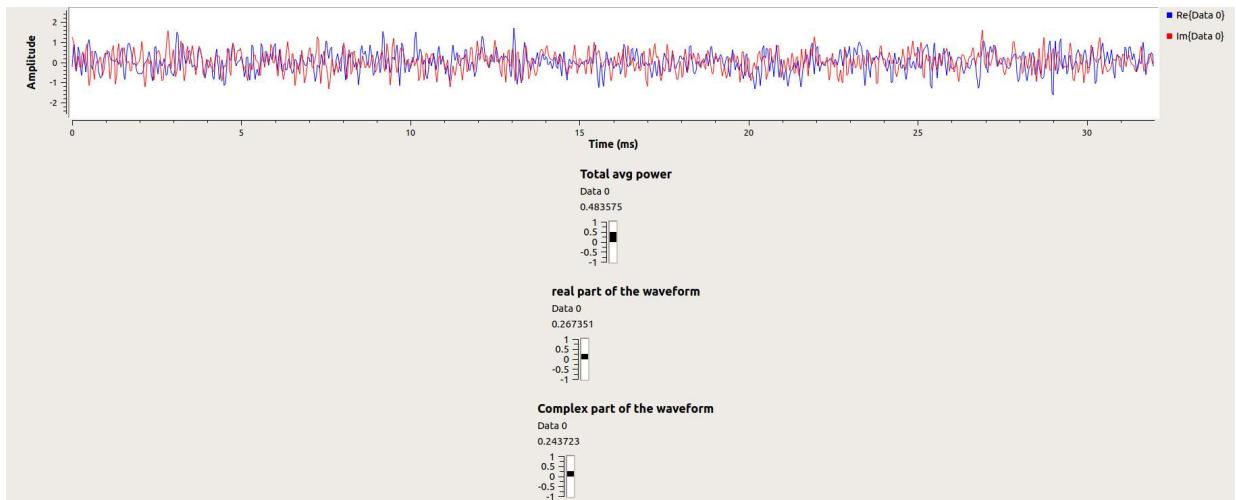
Out[23]:



When we increase the amplitude from 1 to 2 we see that each power measurement has approximately become = 4 (the original measurement).

In [25]: `from IPython.display import Image  
Image(filename='capture.png')`

Out[25]:

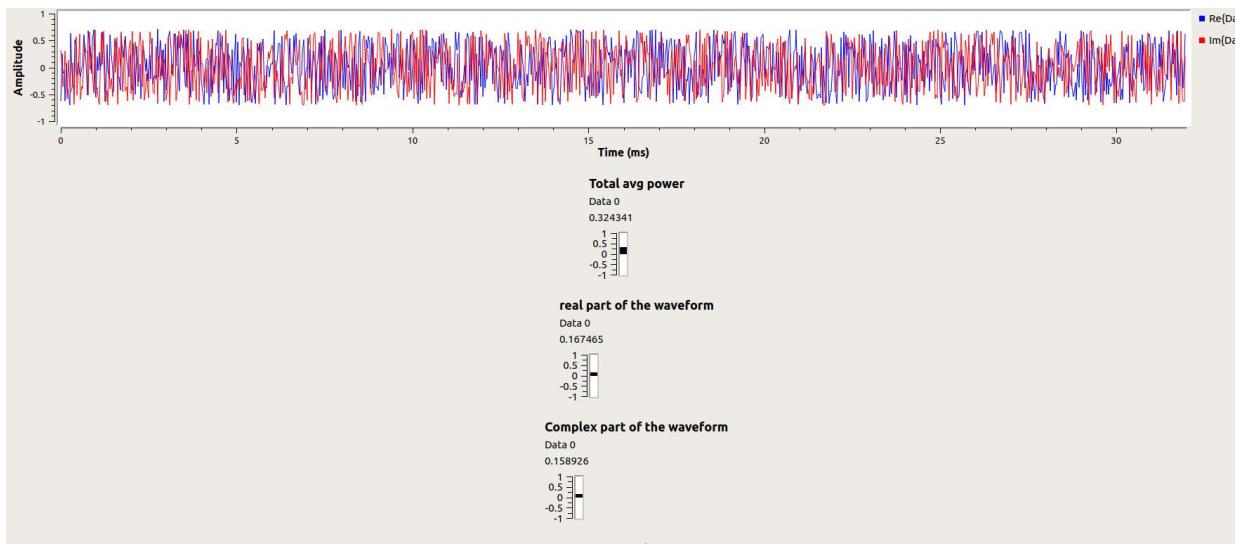


When we decrease the cut off frequency to 8000 from 16000 at amplitude = 1, the power measurements become = 0.5( the power measurements at  $f_l = 16000$ )

For uniform noise of  $A = 1$  and  $F_l = 16000$  the power measurements are shown above. The power in the real part = the power in the imaginary part =  $(1/2)$  of the total average power. The theoretical shape of the amplitude histogram should be a uniform distribution

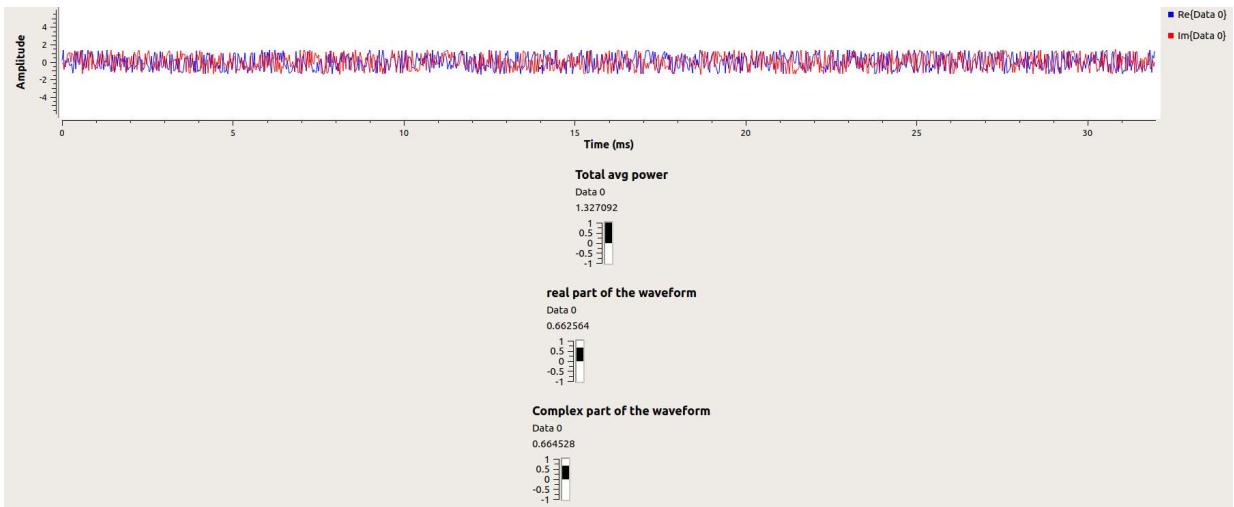
In [26]: `from IPython.display import Image  
Image(filename='capture.png')`

Out[26]:



In [27]: `from IPython.display import Image  
Image(filename='capture.png')`

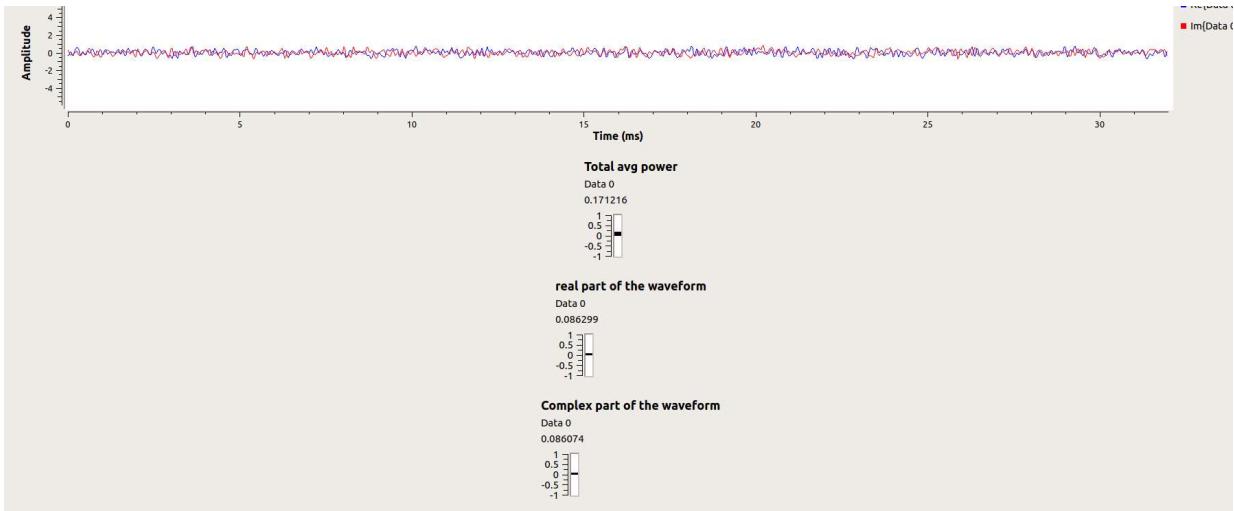
Out[27]:



If the amplitude is increased to  $A = 2$ , the power measurements becomes = 4 (times the original)

In [28]: `from IPython.display import Image  
Image(filename='capture.png')`

Out[28]:



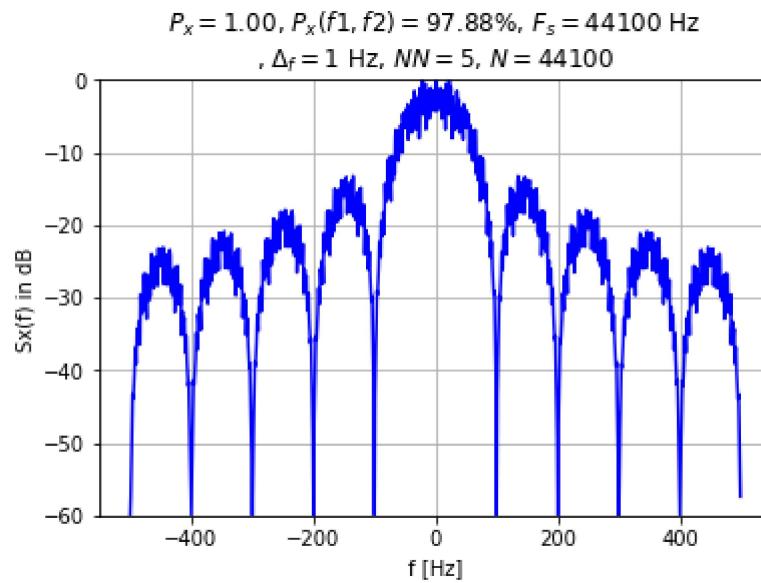
The above measurements are for  $A = 1$  and  $FI = 8000$ . We observe that they are half of the measurements for  $FI = 16000$

We observe that the the power measurements for uniform noise is less than the power measurements for Gaussian noise for the same cutoff frequency and same amplitude. This can be explained by the fact that while uniform noise is uniformly distributed, Gaussian noise is concentrated around a single frequency. Thus for the same bandwidth the total average power contained in that bandwidth is Less for uniform noise.

## Expt 3(a)

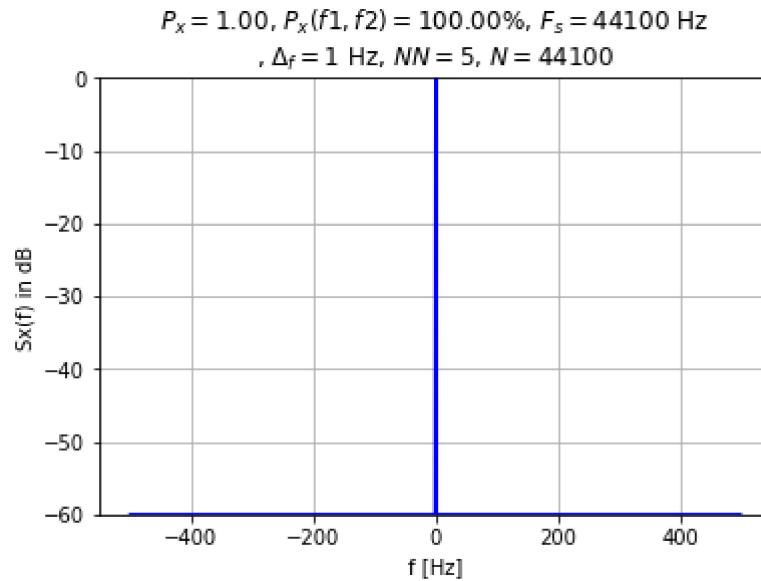
For PAM signal with Rectangular pulse.

In [3]: run Q1C



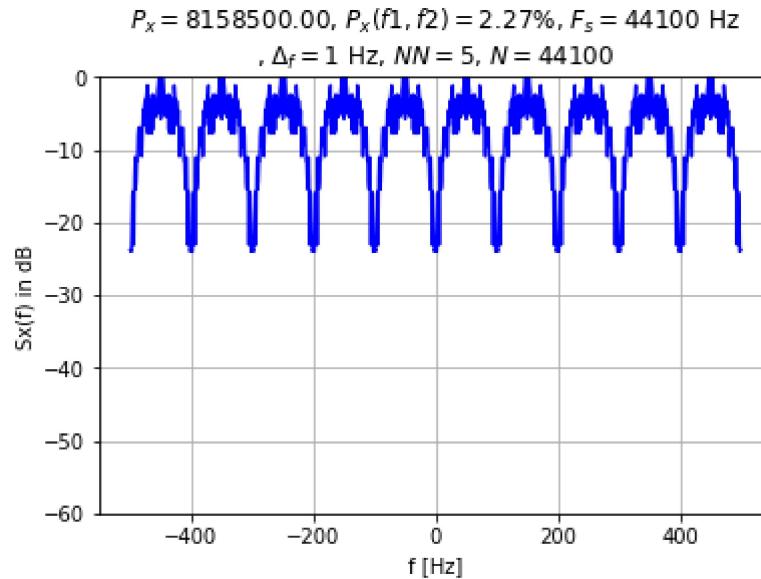
$xt = st^2$  for rectangular pulse PAM signal

In [2]: run Q1C



Derivative of the signal

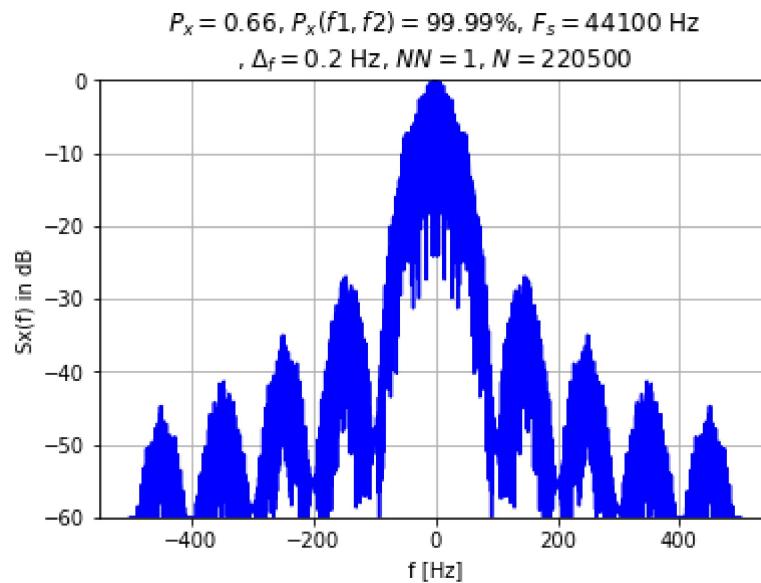
In [2]: run Q1C



By observing the plot for the derivative of the rectangular pulse, We see that it has distinct spectral lines at  $F_b$  which can be used to synchronize the receivers. By looking at the rectangular signal we see that they are not present for  $x_t$  but present for the derivative of  $x_t$

PAM signal with triangular pulse

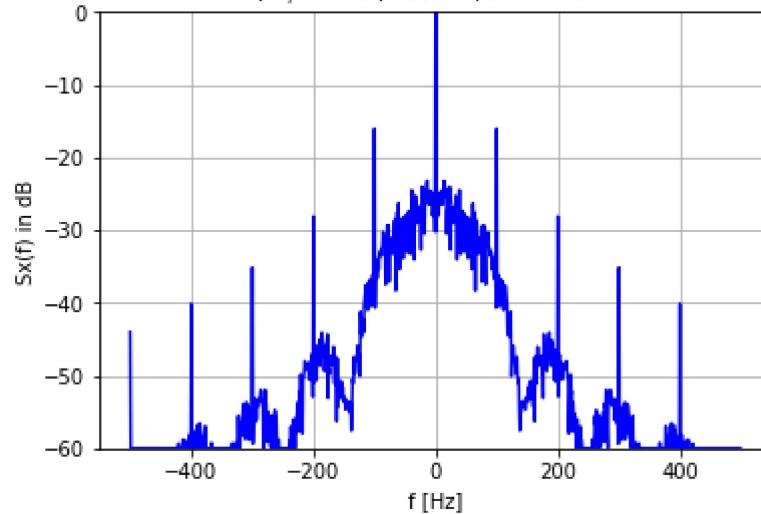
In [19]: run Q1C



Triangular pulse PAM squared

In [3]: run Q1C

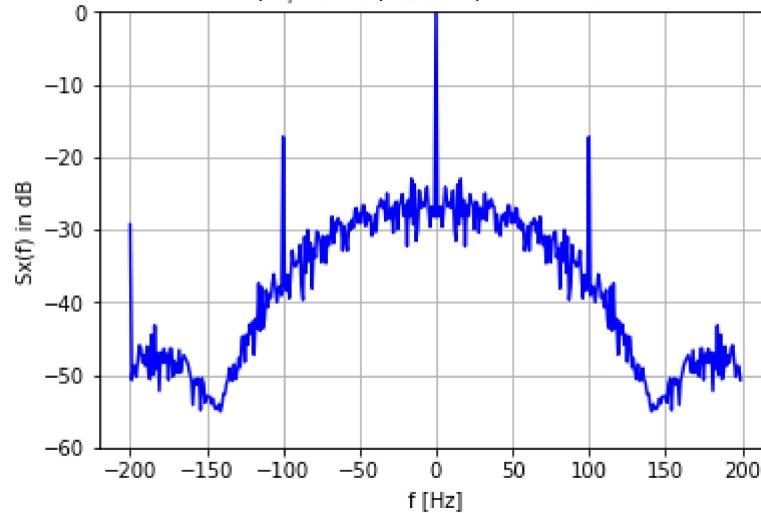
$$P_x = 0.59, P_x(f_1, f_2) = 99.97\%, F_s = 44100 \text{ Hz}, \Delta_f = 1 \text{ Hz}, NN = 5, N = 44100$$



Derivative of the PAM triangular signal

In [4]: run Q1C

$$P_x = 0.63, P_x(f_1, f_2) = 99.77\%, F_s = 44100 \text{ Hz}, \Delta_f = 1 \text{ Hz}, NN = 5, N = 44100$$

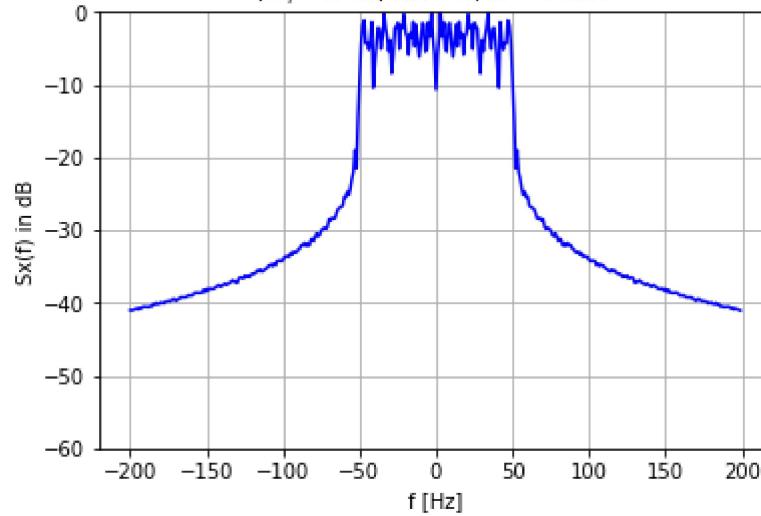


For the triangular signal we observe distinct spectral lines for bot  $xt^2$  and the derivative for  $Xt$ . Hence both can be used for synchronising the receiver

For PAM signal with sinc pulse

In [2]: run Q1C

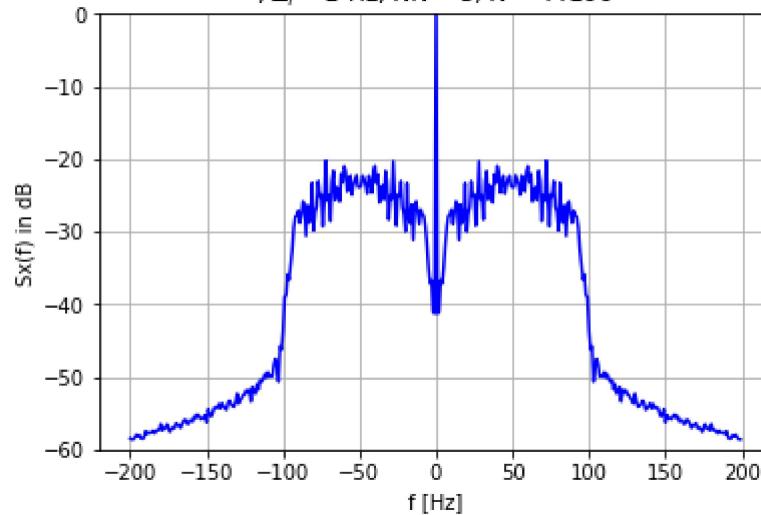
$P_x = 1.00, P_x(f_1, f_2) = 99.94\%, F_s = 44100 \text{ Hz}$   
 $, \Delta_f = 1 \text{ Hz}, NN = 5, N = 44100$



For sinc pulse squared

In [2]: run Q1C

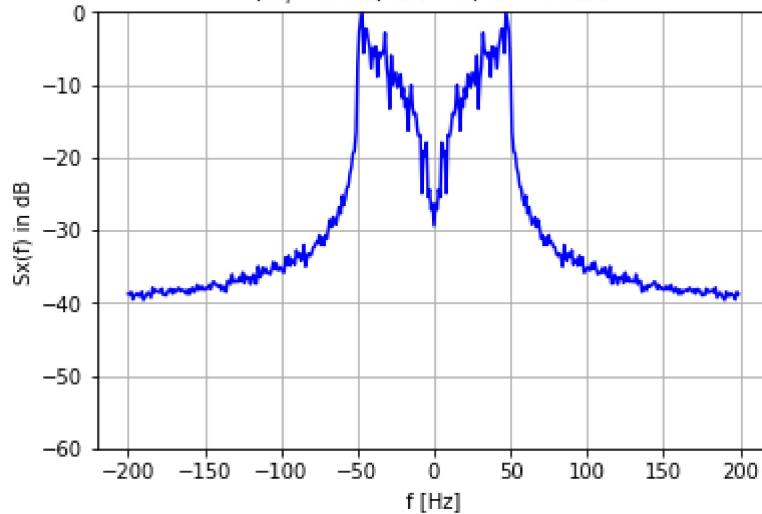
$P_x = 1.61, P_x(f_1, f_2) = 99.97\%, F_s = 44100 \text{ Hz}$   
 $, \Delta_f = 1 \text{ Hz}, NN = 5, N = 44100$



Derivative of sinc pulse

In [2]: run Q1C

$P_x = 38731.98, P_x(f_1, f_2) = 83.18\%, F_s = 44100 \text{ Hz}$   
 $, \Delta_f = 1 \text{ Hz}, NN = 5, N = 44100$

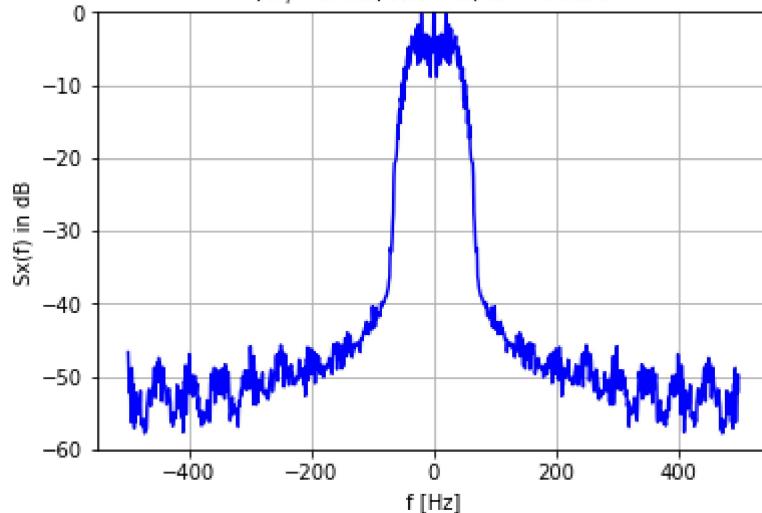


From observing the derivative for the sinc pulse we can tell that there are distinctive spectral lines at  $F_b/2$ . We can use this plot to synchronize the receiver

For RCf PAM signal

In [2]: run Q1C

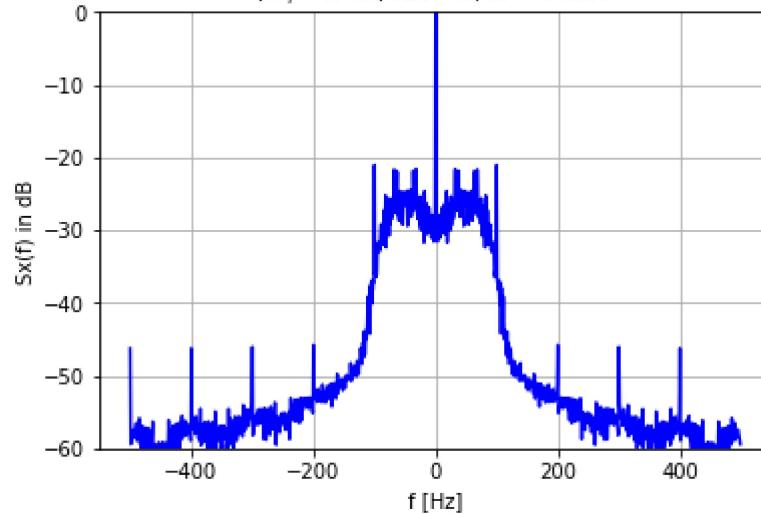
$P_x = 0.87, P_x(f_1, f_2) = 99.49\%, F_s = 44100 \text{ Hz}$   
 $, \Delta_f = 1 \text{ Hz}, NN = 5, N = 44100$



For RCf PAM signal squared

In [2]: run Q1C

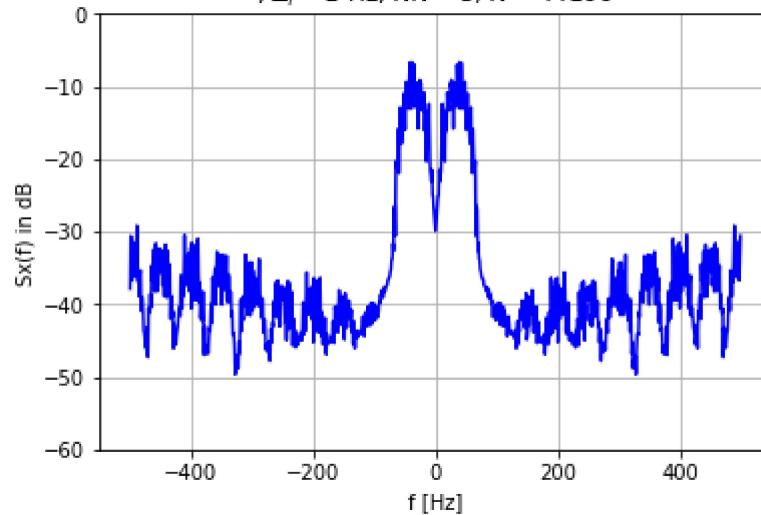
$P_x = 1.07, P_x(f_1, f_2) = 97.00\%, F_s = 44100 \text{ Hz}$   
 $, \Delta_f = 1 \text{ Hz}, NN = 5, N = 44100$



For the derivative of the RCf PAM signal

In [2]: run Q1C

$P_x = 16783332.44, P_x(f_1, f_2) = 0.14\%, F_s = 44100 \text{ Hz}$   
 $, \Delta_f = 1 \text{ Hz}, NN = 5, N = 44100$



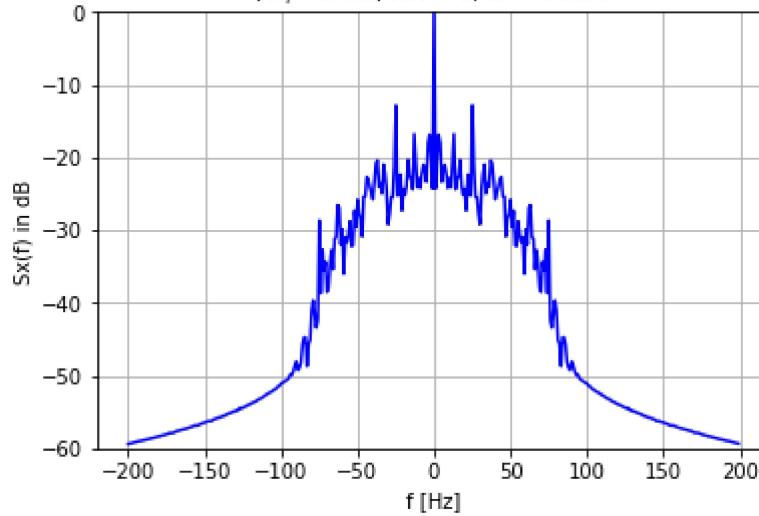
For the RCf signal we observe distinct spectral lines at  $F_b$  for the plot for  $x_t^2$ . This plot can be used to synchronize the receiver

## Expt 3(b)

PSD plot for the square of signal "pamsig401"

In [2]: run Q3B

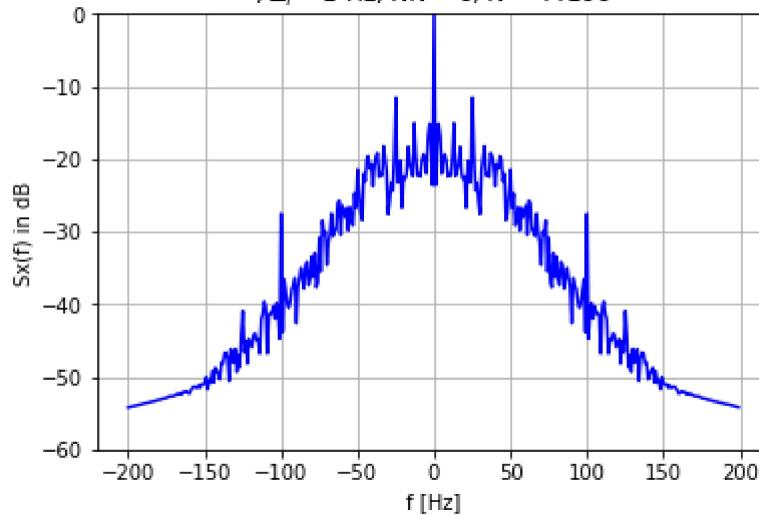
$P_x = 0.26, P_x(f_1, f_2) = 99.97\%, F_s = 44100 \text{ Hz}$   
 $, \Delta_f = 1 \text{ Hz}, NN = 6, N = 44100$



PSD plot for the 4th power of signal "pamsig401"

In [2]: run Q3B

$P_x = 0.14, P_x(f_1, f_2) = 99.93\%, F_s = 44100 \text{ Hz}$   
 $, \Delta_f = 1 \text{ Hz}, NN = 6, N = 44100$

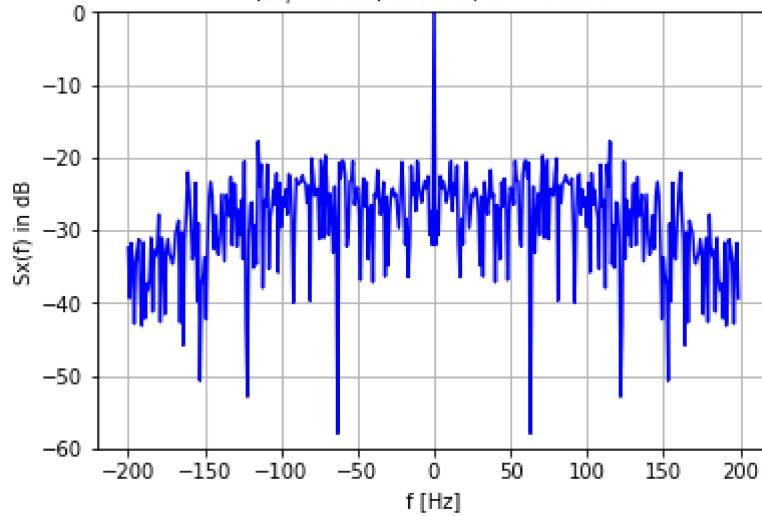


We observe that there is a useful distinctive spectral lines at  $F_b$  for the plot of the 4th power of the signal.

PSD plot for the square of pamsig402

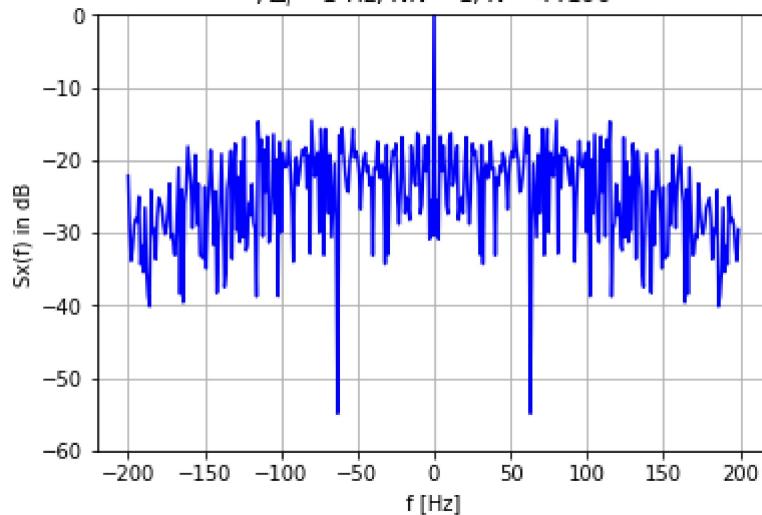
In [2]: run Q3B

$P_x = 0.10, P_x(f_1, f_2) = 99.40\%, F_s = 44100 \text{ Hz}$   
 $, \Delta_f = 1 \text{ Hz}, NN = 1, N = 44100$



In [2]: run Q3B

$P_x = 0.03, P_x(f_1, f_2) = 98.48\%, F_s = 44100 \text{ Hz}$   
 $, \Delta_f = 1 \text{ Hz}, NN = 1, N = 44100$



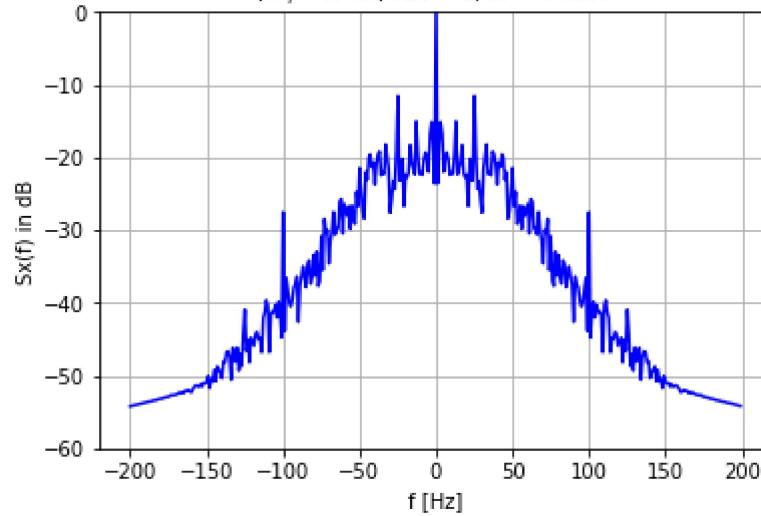
We observe that there is a useful distinctive spectral lines at Fb for the plot of the 2nd power of the signal.

PSD plot for the second power of the signal pr1sig401

In [3]: run Q3B

$$P_x = 0.14, P_x(f_1, f_2) = 99.93\%, F_s = 44100 \text{ Hz}$$

$$\Delta_f = 1 \text{ Hz}, NN = 6, N = 44100$$

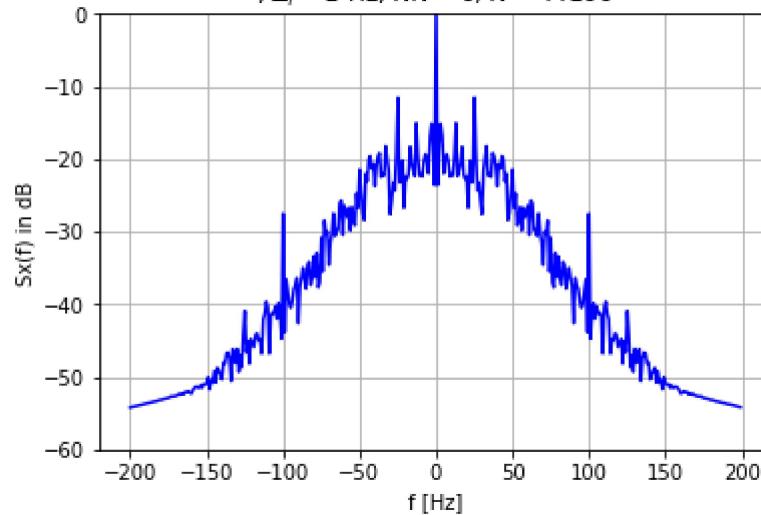


PSD plot for the fourth power of the signal

In [2]: run Q3B

$$P_x = 0.14, P_x(f_1, f_2) = 99.93\%, F_s = 44100 \text{ Hz}$$

$$\Delta_f = 1 \text{ Hz}, NN = 6, N = 44100$$



We observe that there is a useful distinctive spectral lines at Fb for the plot of the 2nd and the 4th power of the signal.