APPLIED SIGNAL PROCESSING LABORATORY

ASSIGNMENT 1

- Paolo Allione s296500
- Camolese Claudio s297378
- Temmuz Sanli s298029

A1.1

A1.1 Energy of a rectangular pulse

Exercise A1.1 can be structured as follows:

- After generating a rectangular pulse signal, plot the pulse on the time axis
- Compute the FFT of the signal in the fundamental interval and then compute the FFT magnitude on the frequency axis
- Compute and plot the percentage of energy contained in the first 10 lobes and then the one contained from 10 to 100 lobes.

Rectangular pulse

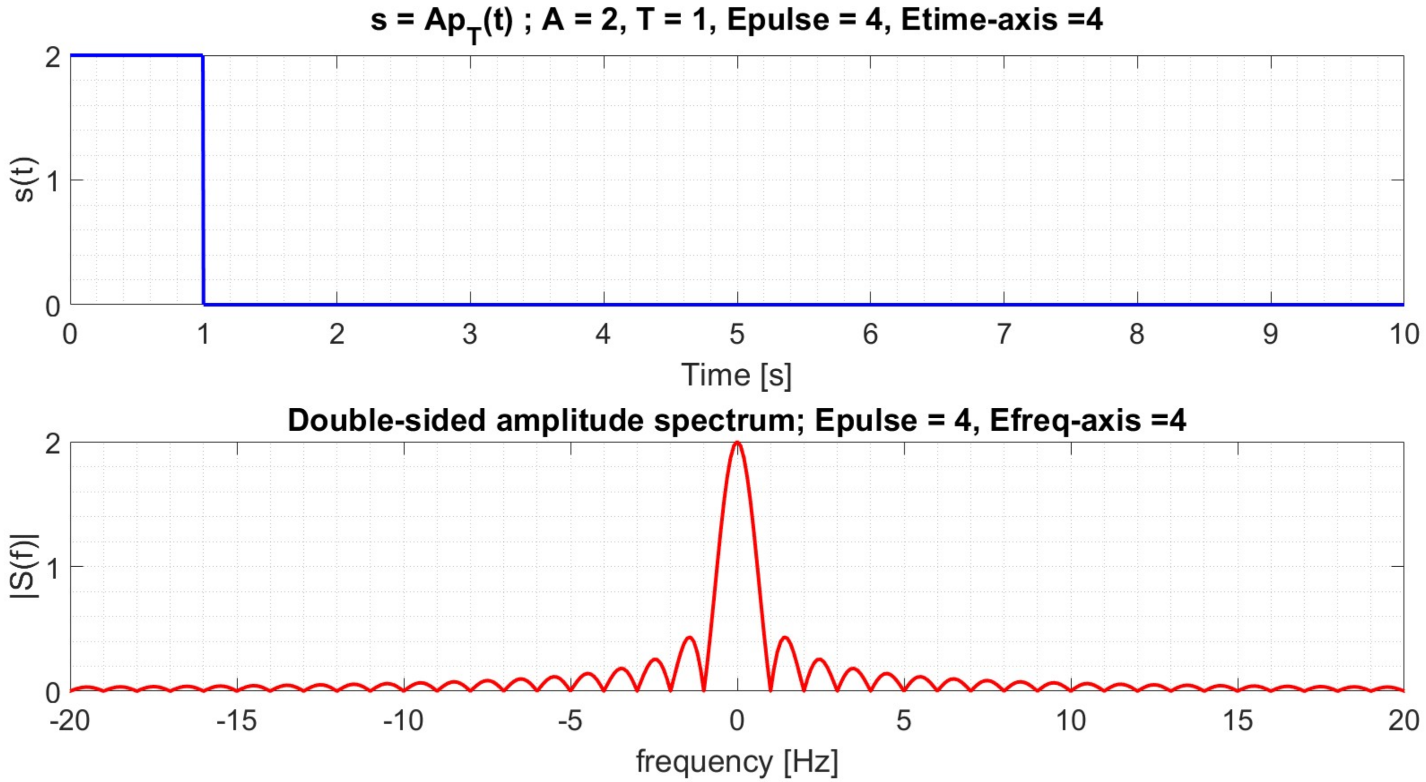
The Matlab figure shows two plots of the signal.

- The upper plot is the rectangular signal with **A**=2 and **T**=1. In the title are present two energy values which are obtained as follow:

$$E_{pulse} = A^2 T$$

$$E_{time} \approx \sum_{k=-\infty}^{+\infty} |x(nT_c)|^2 T_c$$

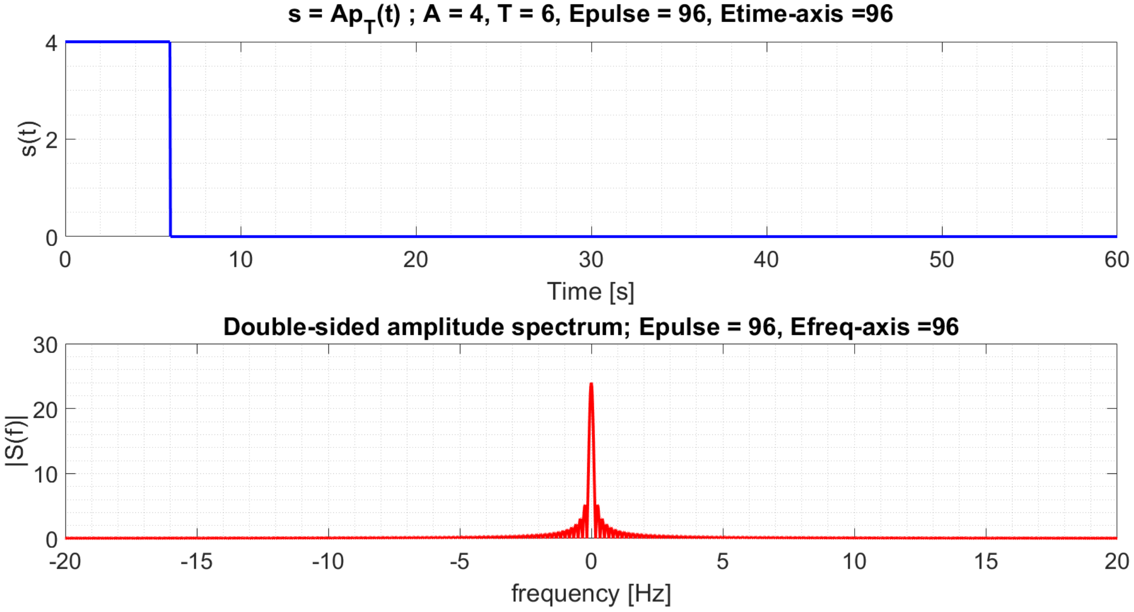
- The second plot shows the magnitude of the Fourier transform of the latter signal on the frequency axis.

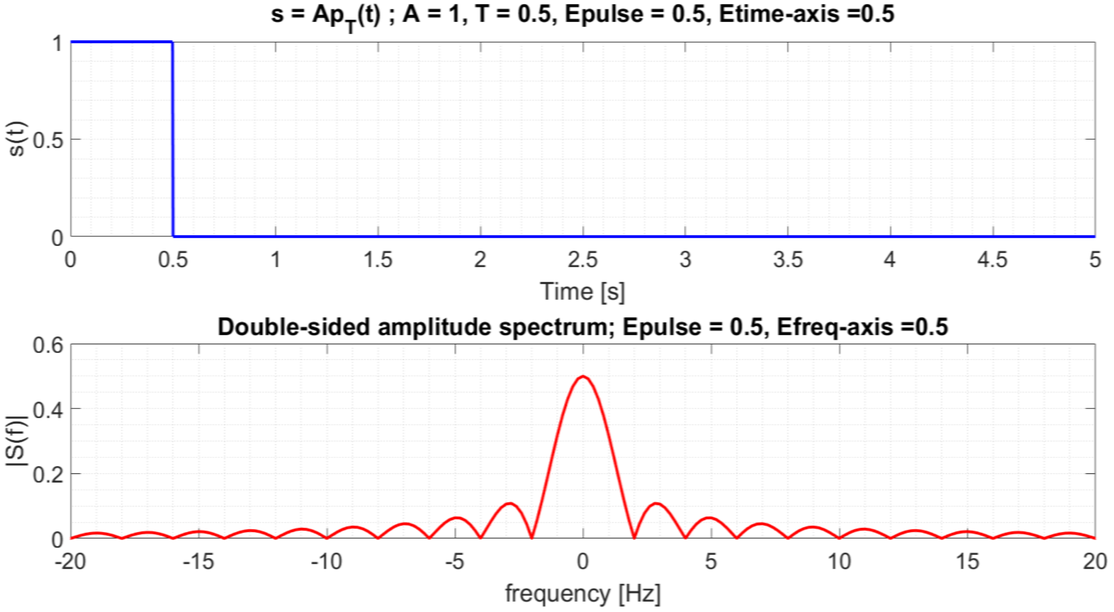


As we can notice from the figure, the Fourier transform of the rectangular pulse is a *sinc* signal. Furthermore, Parseval's identity is verified.

Other examples

By modifying the values of A and T, two examples of the signal and its Fourier transform are shown.





Decreasing the frequency leads to narrower lobes in the frequency spectrum and in a higher value of the energy due to concentration.

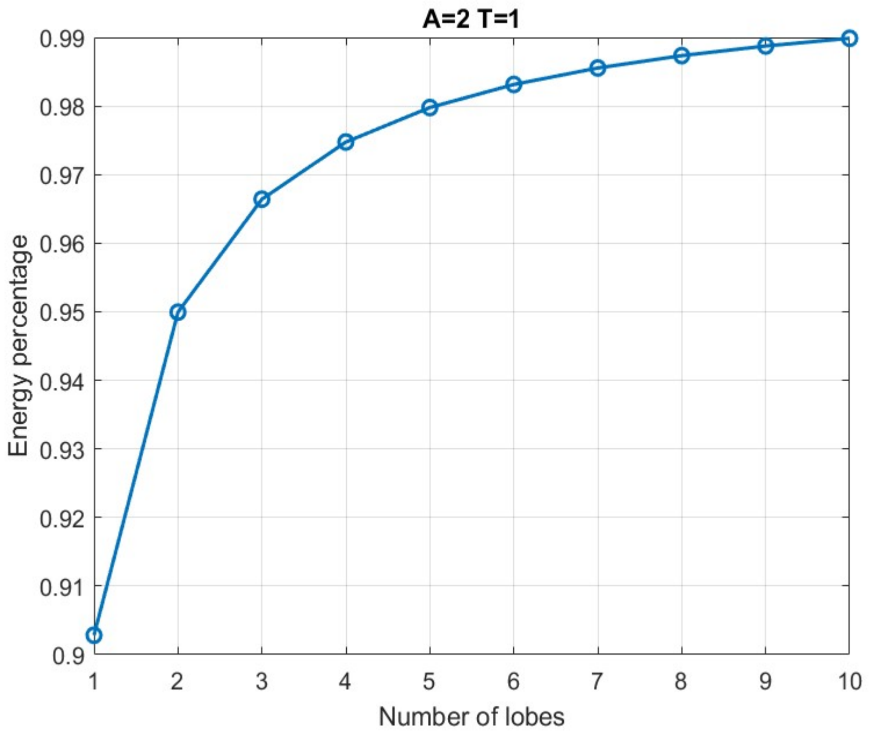
Increasing the frequency leads to wider lobes in the frequency spectrum and in a lower value of the energy due to the dispersion.

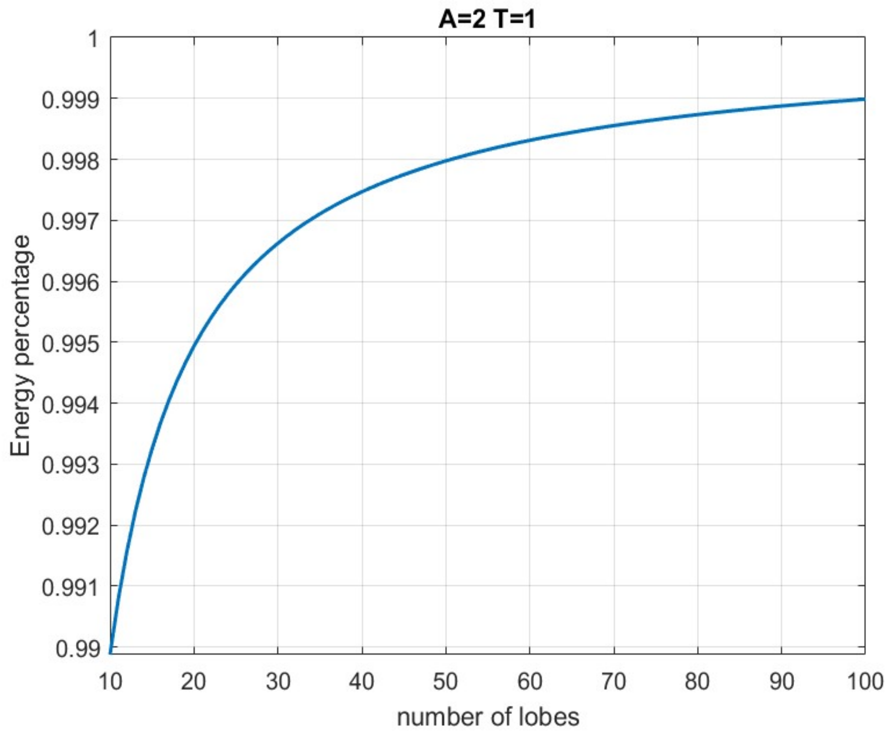
Energy in lobes

The goal of this section is to compute and plot the percentage of energy contained in 10 lobes and then in the range from 10 to 100.

The lobes are useful because they are linked to a specific frequency and show how much energy is distributed in these frequencies.

Taking advantage of the spectrum symmetry, it is sufficient to double the energy in the positive frequency axis and compute the result.





As it can be observed, the greatest contribution of energy is produced by the first 10 lobes. The more lobes we consider, the more their contribution becomes negligible.

Because of that, the total energy of a rectangular pulse is, in first approximation, contained in the first lobe.

A1.2

A1.2 Filtering of 3 sines on the frequency axis

SIGNAL GENERATION

Our composite signal is formed by summing three sinusoidal signals with different frequencies and random phases:

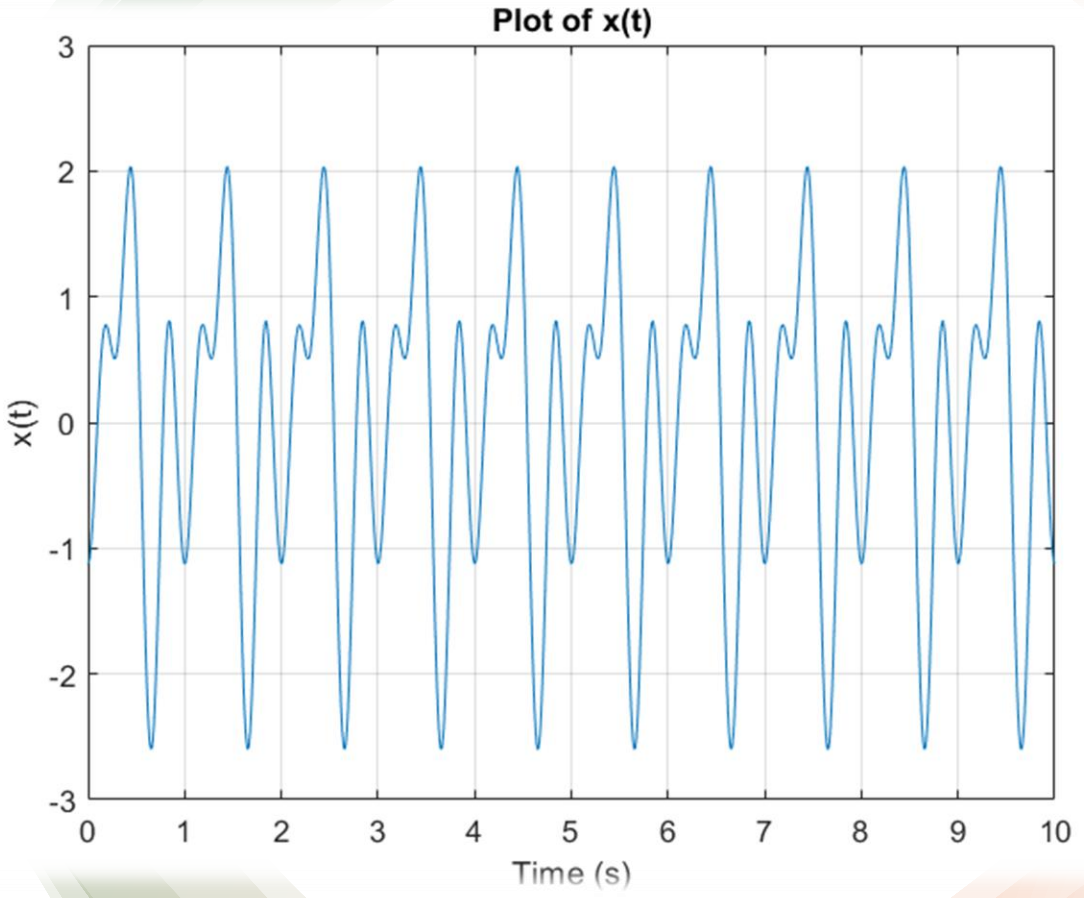
$$x(t) = \sin(2\pi fAt + \phi A) + \sin(2\pi fBt + \phi B) + \sin(2\pi fCt + \phi C)$$

Here, fA=1, fB=2, and fC =3 represent the frequencies of the sinusoidal signals, while ϕA , ϕB and ϕC are random phases.

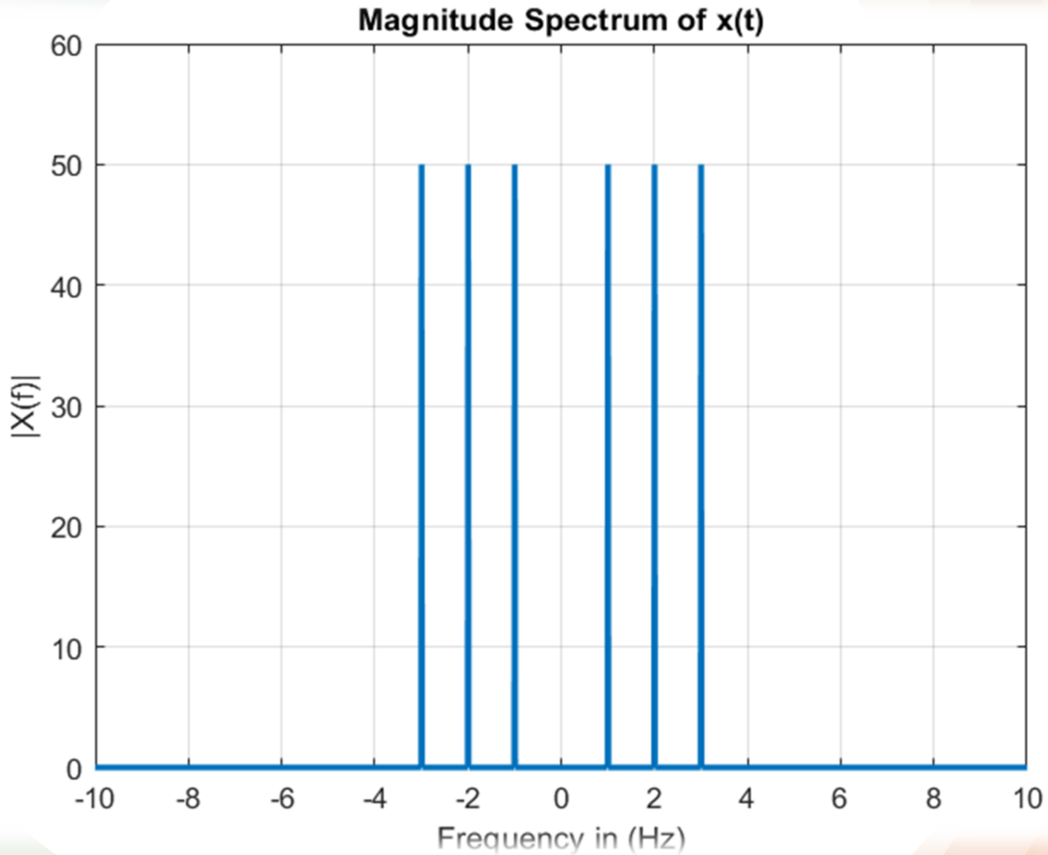
Time-Domain Analysis

We begin by plotting the composite signal in the time domain, which allows us to visualize its waveform and amplitude variations.

The composite signal shows periodic behavior with special patterns corresponding to the individual sinusoidal components.



Frequency-Domain Analysis

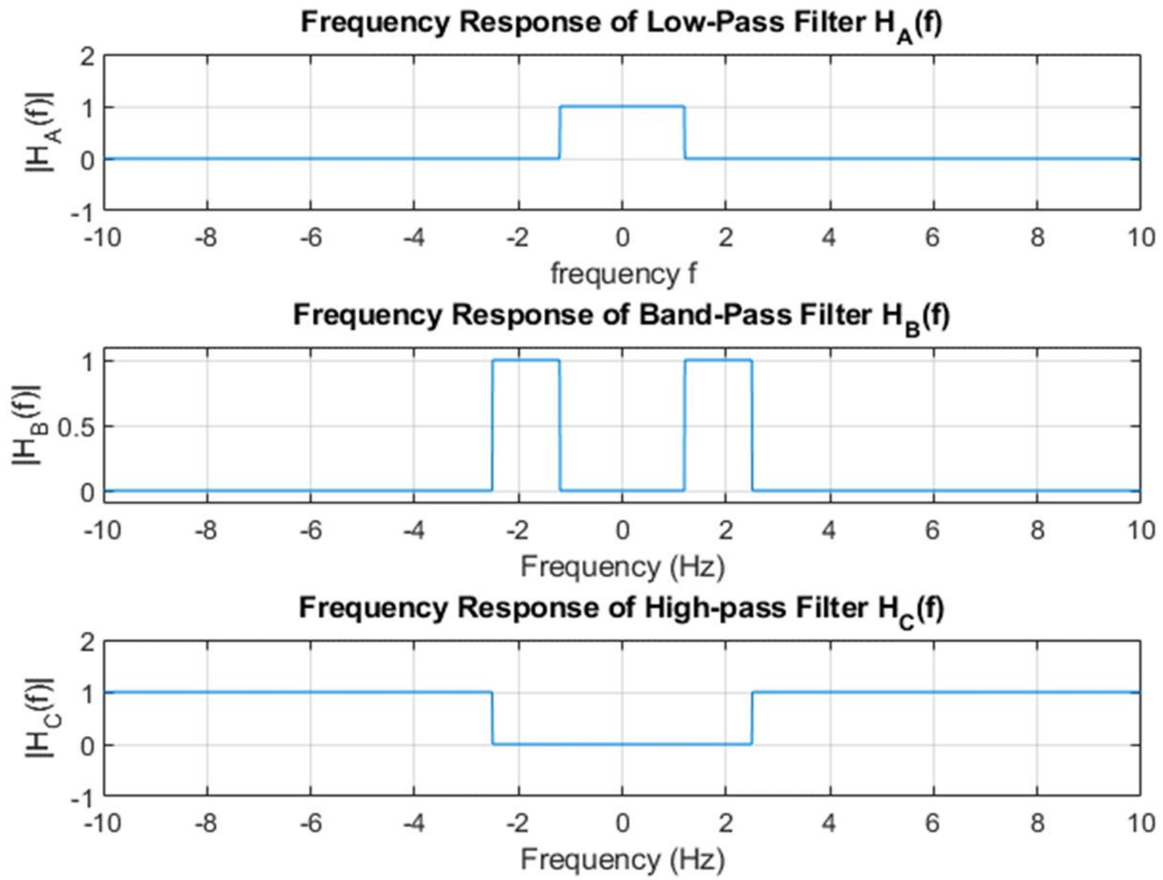


- Next, we analyze the frequency content of the composite signal by computing its Fourier transform and plotting the magnitude spectrum.
- The peaks in the spectrum correspond to the frequencies of the individual sinusoidal signals, providing insights into their presence and magnitude.

Filter Design:

To isolate each sinusoidal signal, we design specific filters: a low-pass filter $HA(f)$ for fA, a band-pass filter $HB(f)$for fB , and a high-pass filter $HC(f)$ for fC .

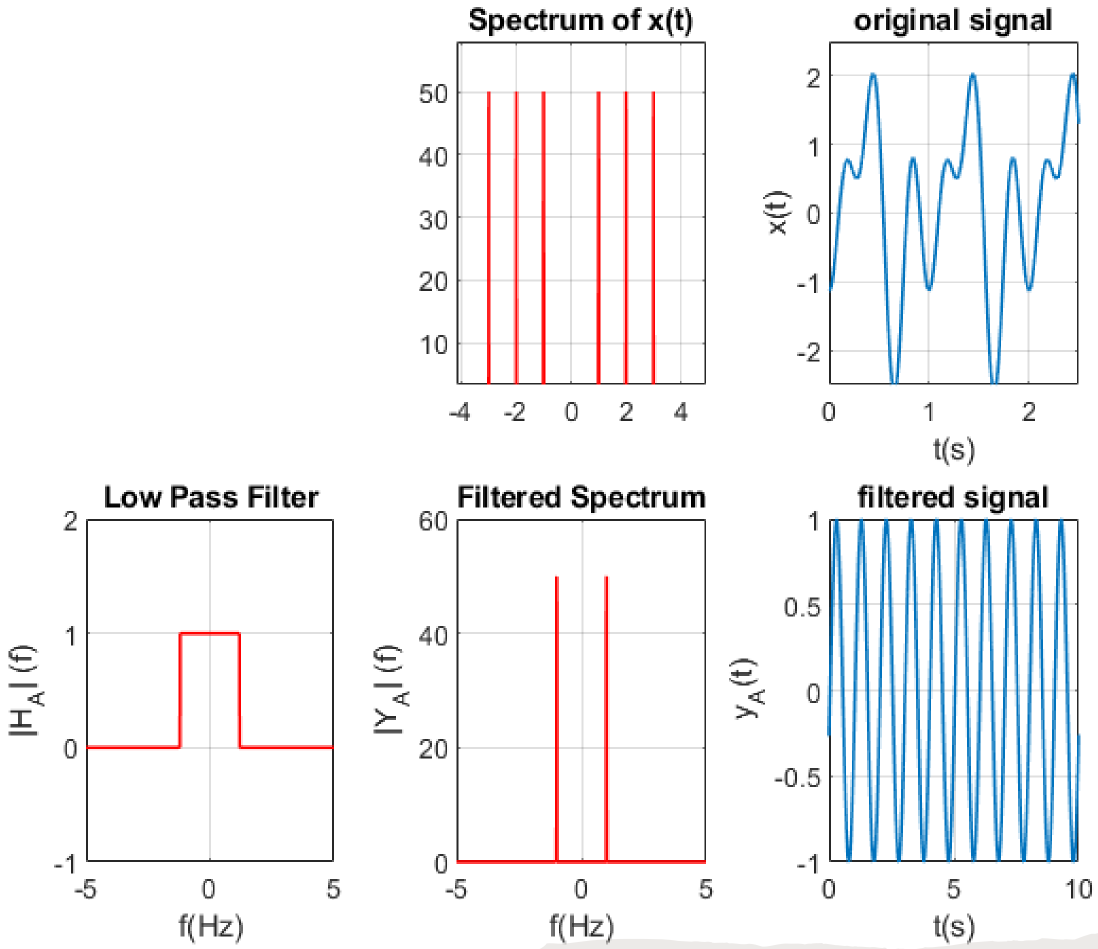
These filters are designed to selectively pass the desired frequency components while preventing others.



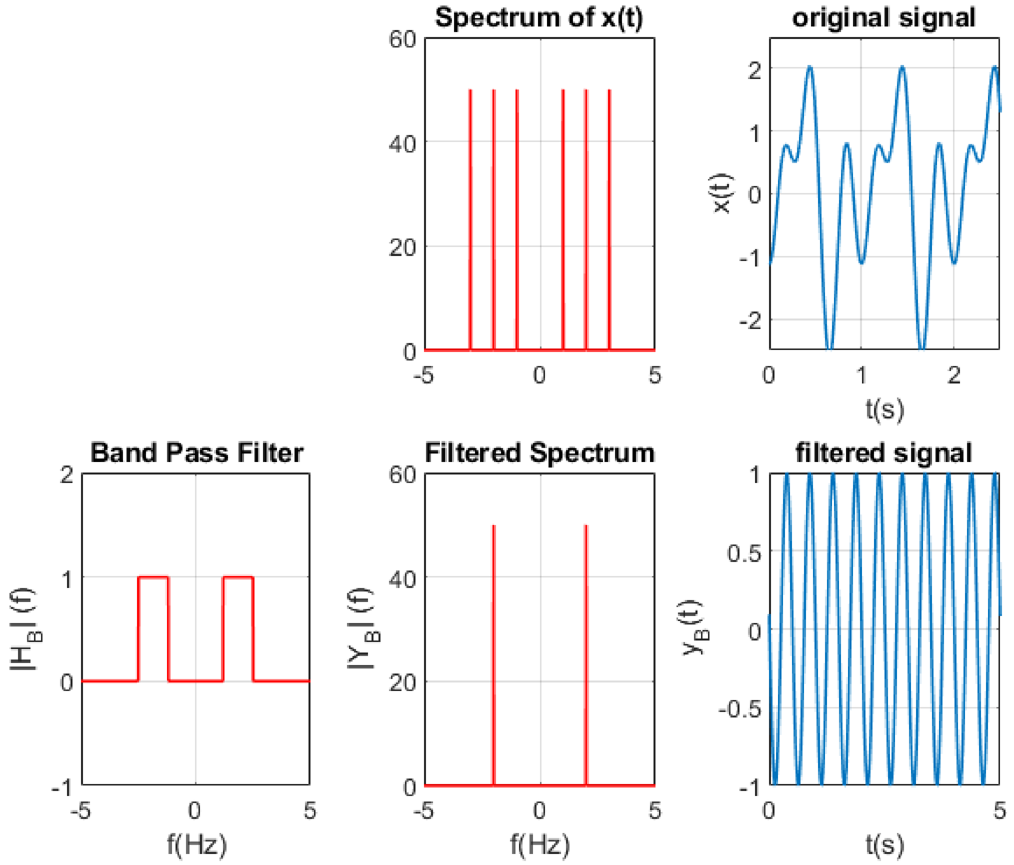
IFFT and Filtered Signals

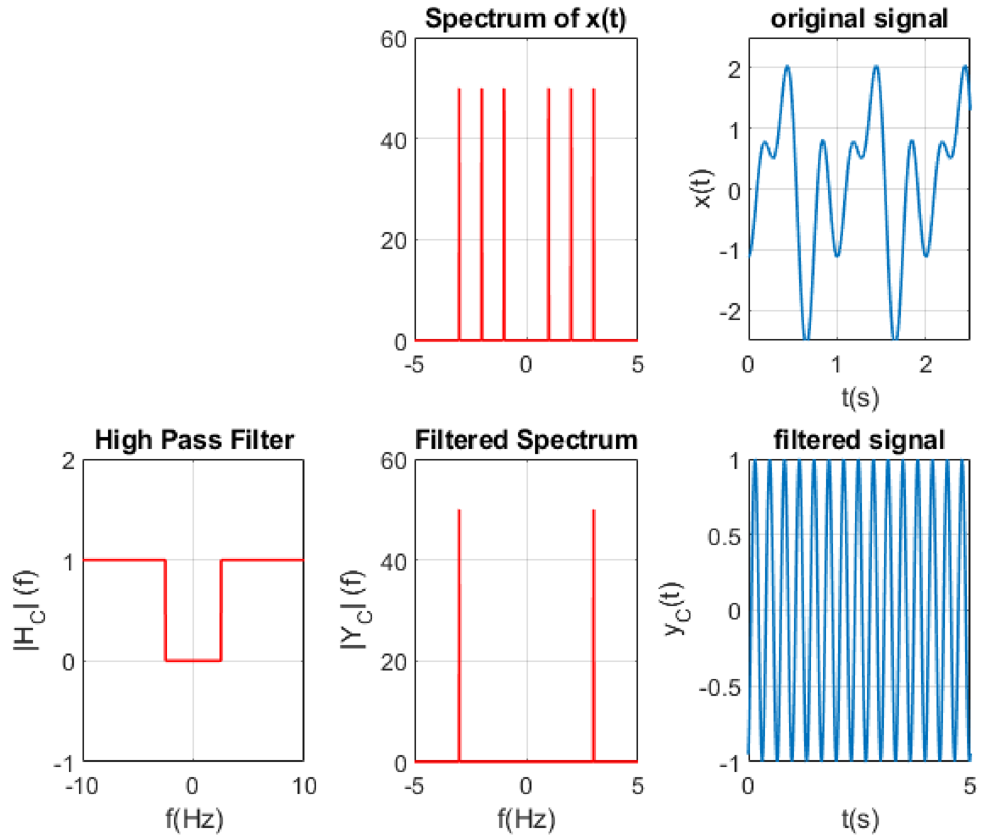
We take each filter to the composite signal by multiplying its frequency response with the inverse Fourier transform of the signal.

This process separates the desired sinusoidal components, yielding filtered signals corresponding to fA, fB and fC.



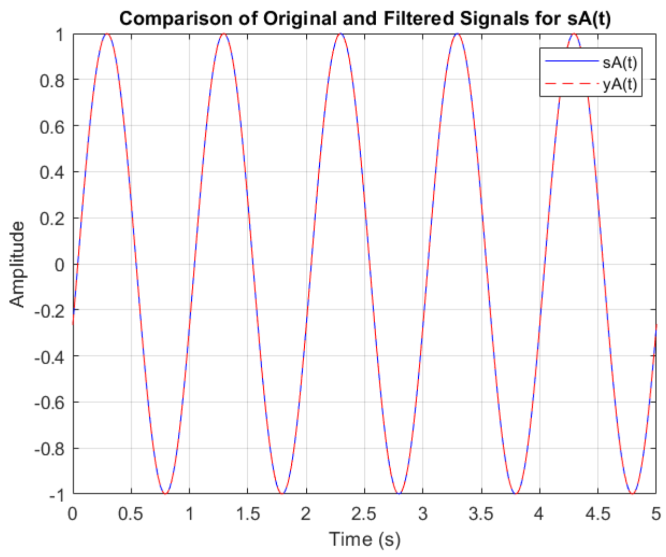
Other Signals

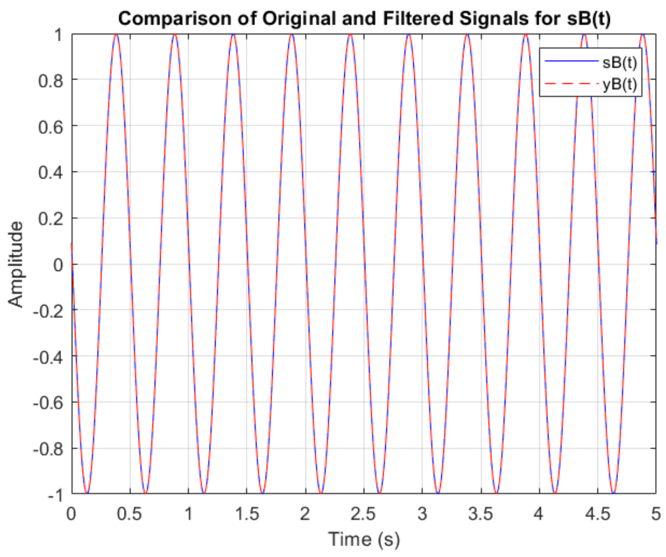


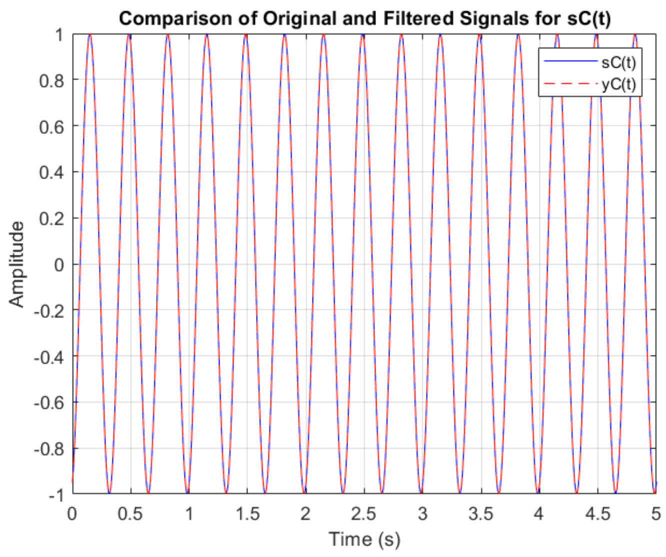


Verification

To confirm the accuracy of the filtered signals, we compare them with the original sinusoidal signals. This validation step guarantees that the filtering process maintains each component signal.







A1.3

A1.3 Quantization

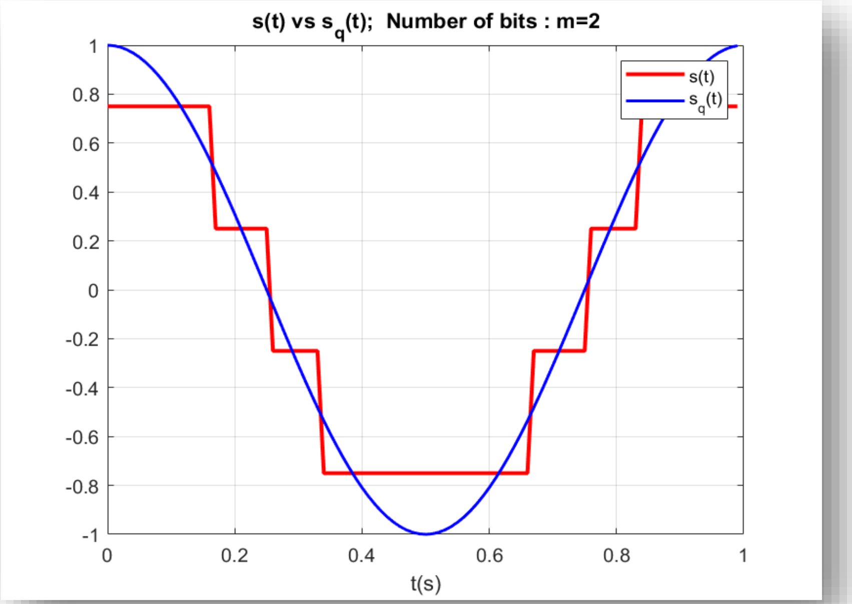
Exercise A1.3 can be structured as follows:

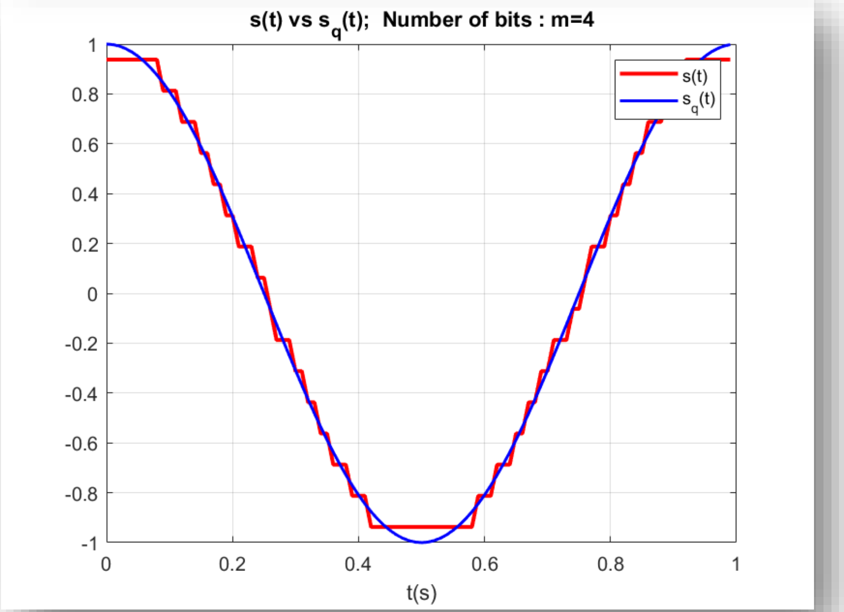
- After generating a sinusoidal signal, plot the original signal s(t) and the quantized signal $s_q(t)$.
- Compare the spectrum of the original and the quantized signal in dB.
- Compute the SNR of the signal.

Quantized signal

The two plots consider the original signal and compare it with the quantized signal obtained with m=2 and then m=4, where m is the number of bits.

As it can be observed, the more bits we use the more the quantized signal is similar to the original.





Spectrum analysis

The figure compares the spectrum of the original and quantized signal. The values are plotted in [dB].

The **SNR** value is also presented.

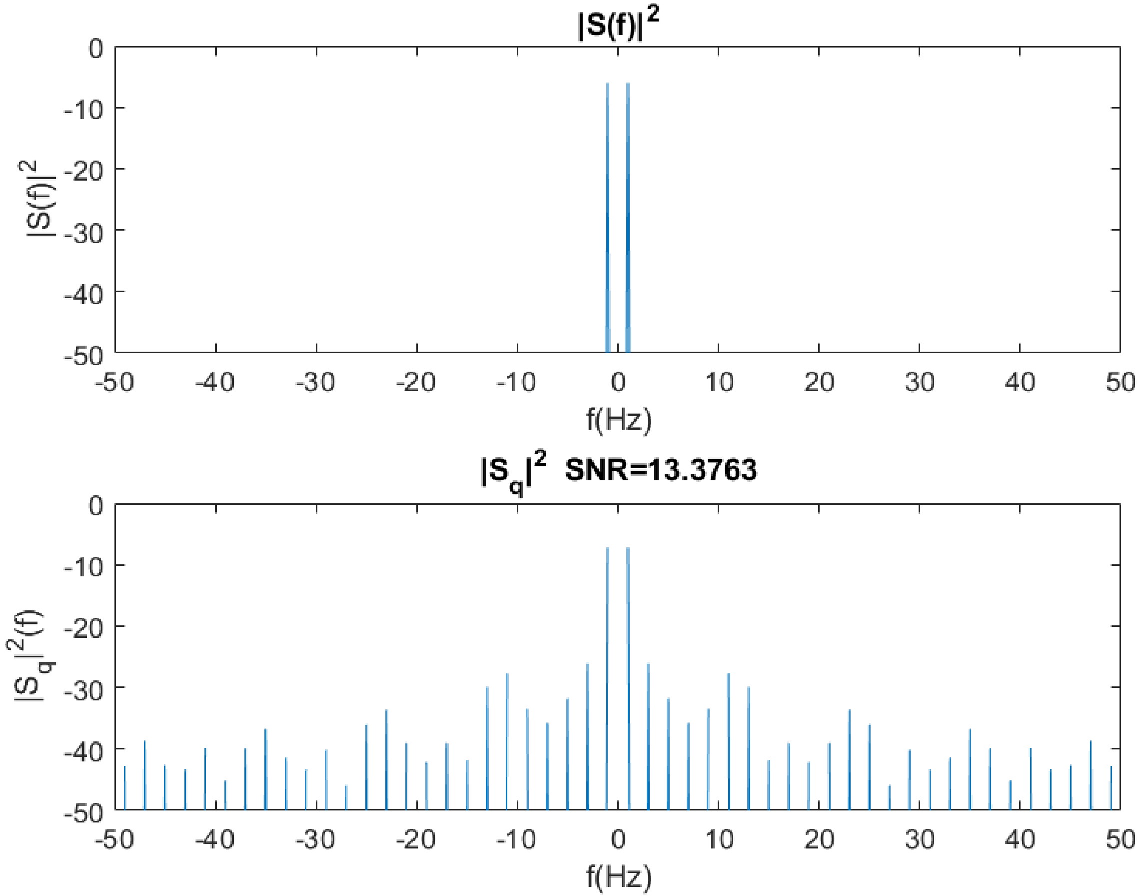
SNR (Signal-Noise-Ratio) is a measure of the quality of a signal and indicates how strong the signal is relative to the background noise present.

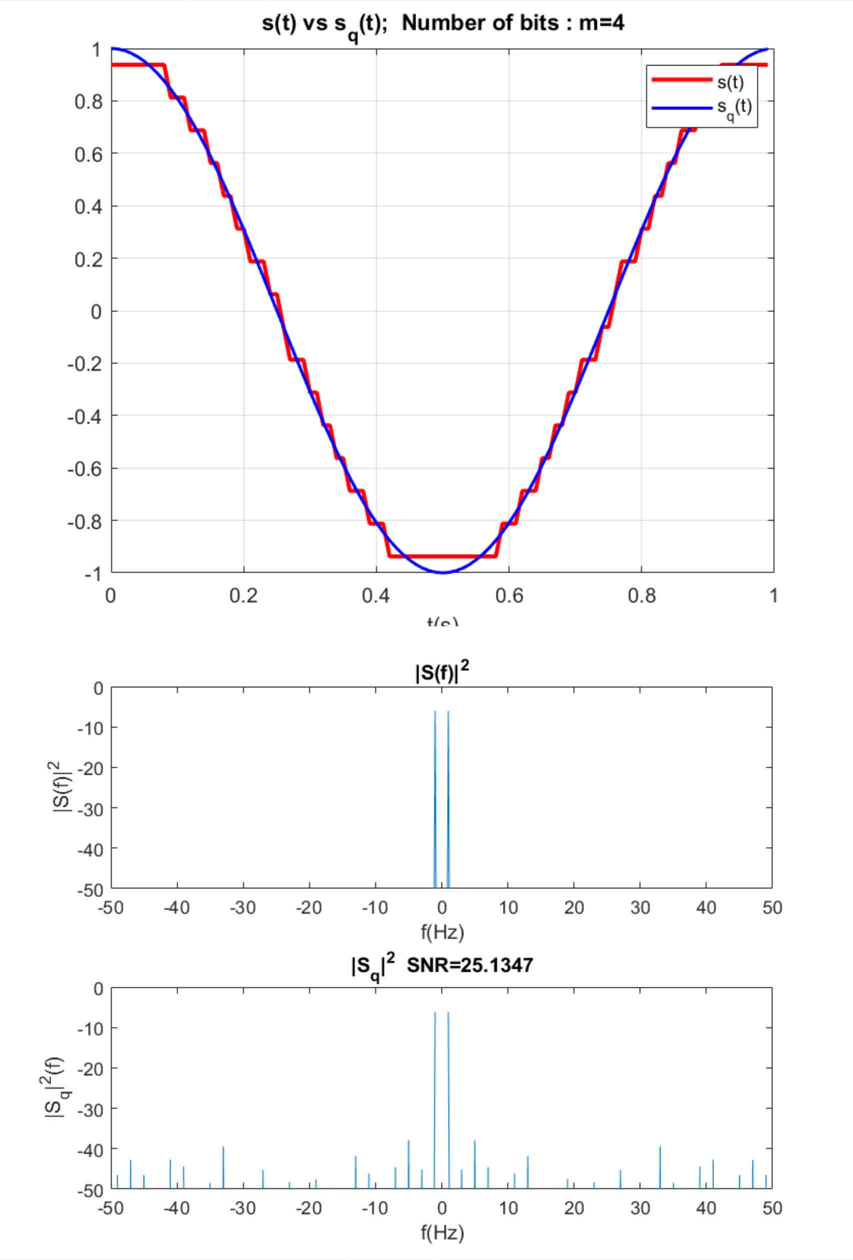
It has been obtained using the known formula:

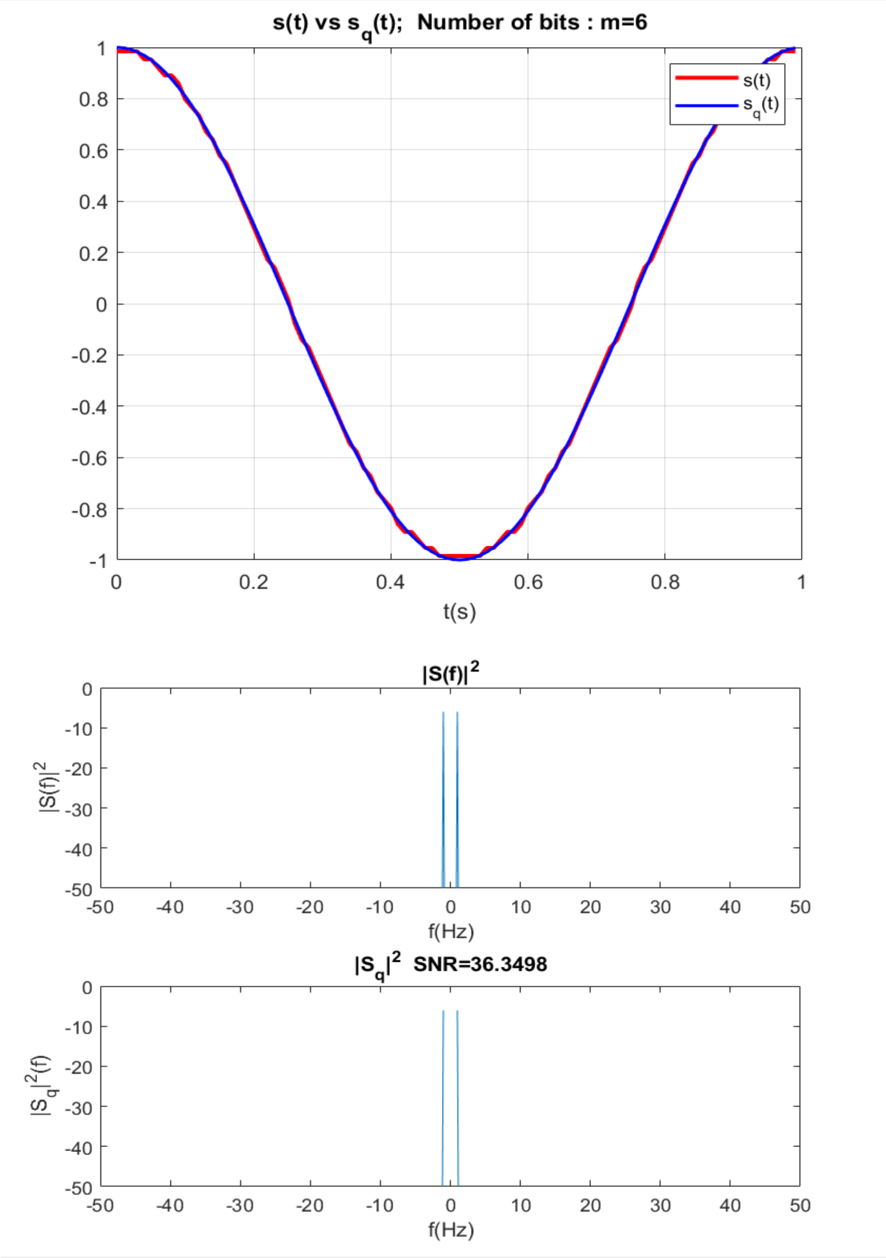
$$SNR = 10\log_{10}\frac{E_s}{E_{\cdot n}}\ [dB]$$

According to the formula, the higher is the **SNR** value, the higher is the quality of the signal.

Furthermore, to obtain the noise components, a filter has been used for isolating $f \neq f_0$ components.







These other examples represent the quantized signal with different values of m.

As said before, the higher is m, the more accurate is the quantized signal compared to the original and the noise contribution becomes more negligible.

Furthermore, the SNR relation is verified.

$$SNR = 6m\,[dB]$$