

# SE 380 — P1

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## 1 Task 1

To run the code properly and plot all the figures copy the code into a jupyter notebook and run each plot cell individually.

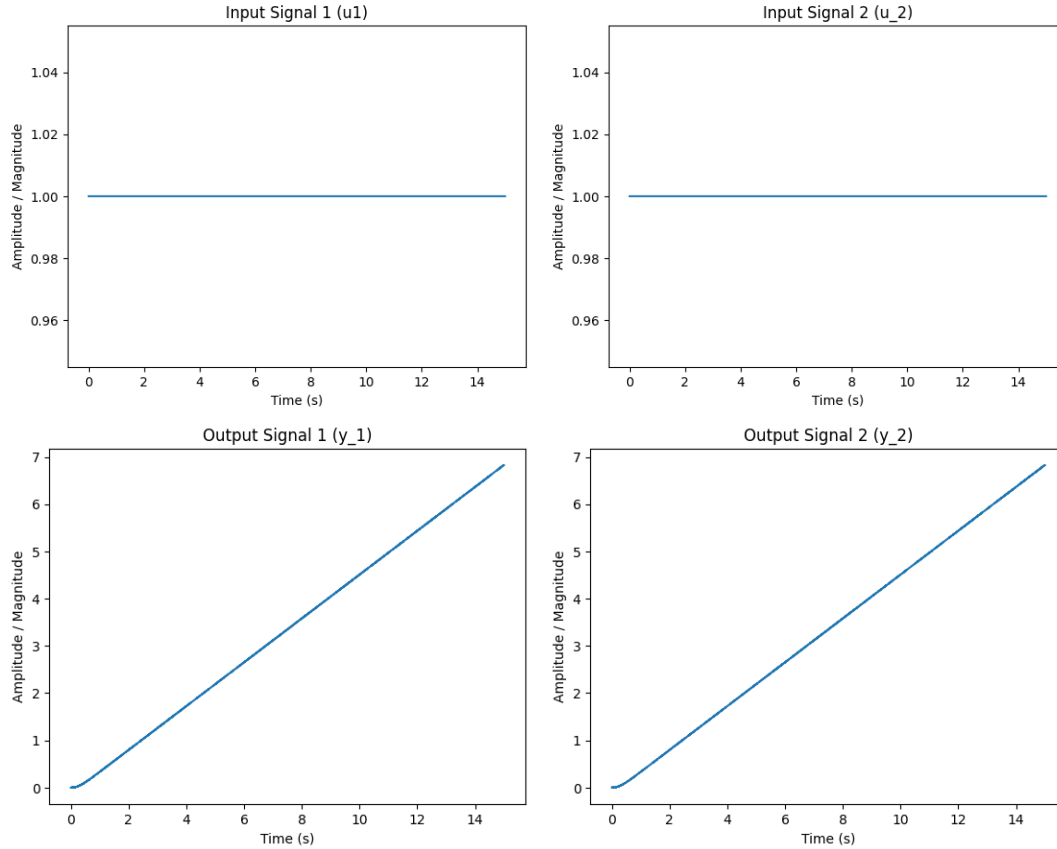
### 1.1 Item 1

Our inputs  $u = [u_1, u_2]^T$  are constant values of 1 over a time period of 15 seconds where one timestep lasts 0.001s. In numpy, we can represent this as a two-dimensional vector of length 15,000: `u = np.ones((15,000, 2))`.

We can generate the two output signals  $y = [y_1, y_2]^2$  by passing the inputs through the simulator `y = sm.sim(u)`

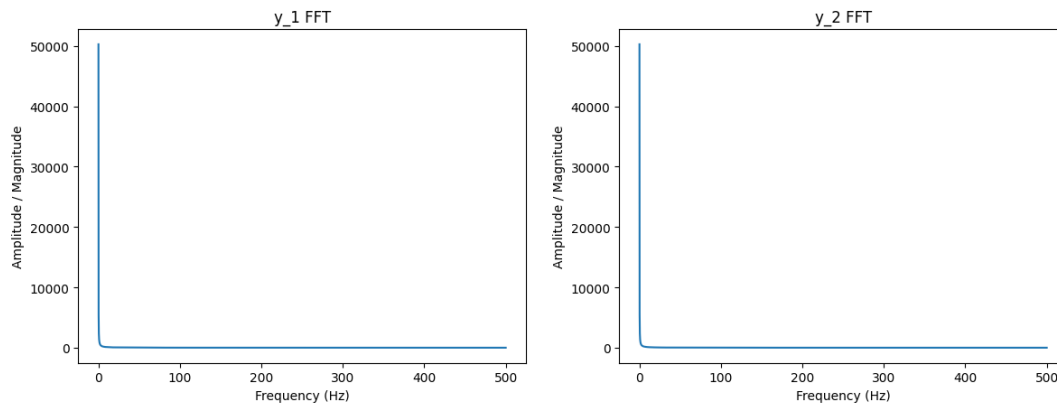
### 1.2 Item 2

We plot the two input signals and two output signals below:



### 1.3 Item 3

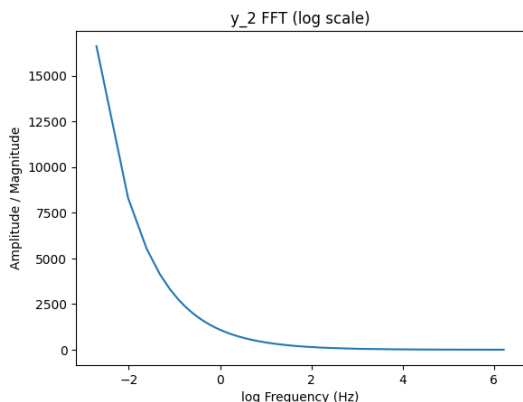
To plot the frequency spectrum of the output signals we use `np.fft.fft()` to compute the discrete Fast Fourier Transform on the output signals. Note that we do not plot the negative frequencies (the second half of the output of `np.fft.fft()`) and that we can plot the magnitude of the complex numbers returned by `np.fft.fft()` using `np.abs()`.



### 1.4 Item 4

We're going to choose a frequency cutoff to filter out any frequencies larger than  $\omega_c$ . To do this, note that most of the total energy of the signal is concentrated in frequencies close to zero with a long tail of high frequency components that don't significantly contribute to the signal. Lets plot

the same graph but with the frequencies on a log scale (note that this is using `np.log`, which uses base  $e$ ):



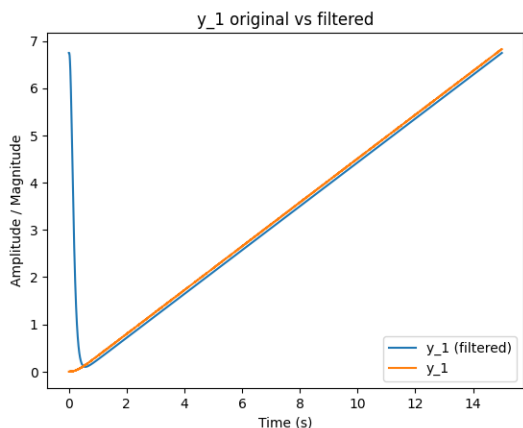
Looking at this graph, we can see that some reasonable values for  $\omega_c$  could be somewhere around the  $e^0$  to  $e^2$  range since the overwhelming majority of the energy of the signal is already below zero log-frequency. We'll choose  $\omega_c = e^1$  as a middle ground for our low pass filter.

## 1.5 Item 5

We'll follow the approach in class and design a low-pass filter as a transfer function in the Laplace/Fourier domain of the format  $\frac{1}{(s\tau + 1)^3}$ , where  $\tau = \frac{1}{\omega_c}$  is our time constant and  $s$  is the Laplace input variable. Since the question asks us to design a third-order filter with multiple real poles that are coincident, we can see that our transfer function has three real poles, all at the same spot due to the cubed term.

## 1.6 Item 6

Since our chosen  $\omega_c$  frequency taken from inspecting the graph is in Hertz we will convert it to radians/s and then take the reciprocal to get  $\tau$ :  $\tau = \frac{1}{2\pi\omega_c} = \frac{1}{2\pi}$ . We can then apply the filter by computing the output signals to the Laplace/Fourier domain, multiply them by the transfer function, then convert back to the time domain using the Inverse Fast Fourier Transform. We can do this using the `np.fft.ifft()` function.



Looking at the original vs filtered signals, we can see that the filtered signal is a good approximation of the original signal, but with some differences near the beginning due to the lack of

high-frequency components.