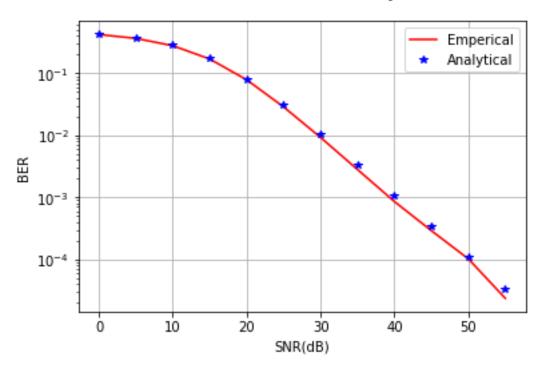
```
1. import numpy as np

    import numpy.random as nr
    import matplotlib.pyplot as plt

4.
5. No = 1
6. SNRdB = np.arange(0, 60, 5)
7. SNR = 10**(SNRdB/10)
8. Eb = (SNR*No)/2
9. BER = np.zeros(len(SNRdB))
10. BERt = np.zeros(len(SNRdB))
11.
12. nBlocks = 1000
13. N = 64
                           # subcarriers
14. L_tilda = 10
                           # cyclic prefix Length
15. L = 3
                           # channel taps
16.
17. Overlap1 = np.zeros(L-1)
18. for blk in range(nBlocks):
19.
        bitsI = nr.randint(2, size = N)
        bitsQ = nr.randint(2, size = N)
QPSKsym = (2*bitsI - 1) + 1j*(2*bitsQ - 1)
21.
        h = nr.normal(0, np.sqrt(1/2), L) + 1j * nr.normal(0, np.sqrt(1/2), L)
22.
        h_pad = np.pad(h, (0,N-L), 'constant')
23.
        noise = nr.normal(0, np.sqrt(No/2), N+L_tilda+L-1) + nr.normal(0, np.sqrt(No/2),
   N+L_tilda+L-1)
        H = np.fft.fft(h_pad)
25.
        for snr in range(len(SNRdB)):
26.
27.
            X = QPSKsym * np.sqrt(Eb[snr])
                                                   # frequency domain samples
            x = np.fft.ifft(X)
28.
                                                   #time domain samples
            CP = x[N-L_tilda:]
                                                   #cyclic_prefix
29.
30.
            x_t = np.concatenate((CP, x))
                                                   #cyclic prefix + samples
31.
            y_rx = np.convolve(x_tx,h) + noise
32.
            y_rx1= y_rx[0:N+L_tilda]
33.
            y_rx2 = y_rx[N+L_tilda:]
            y_rx1[0:L-1] = y_rx1[0:L-1] + Overlap1
34.
35.
            Overlap1 = y_rx2
                                                  # save overlap part
36.
            #removal of CP
37.
            ofdm_rx = y_rx1[L_tilda:]
            Y = np.fft.fft(ofdm_rx)
38.
39.
            Y_eq = Y/H
40.
            X_decI = (np.real(Y_eq)>0)
            X_{decQ} = (np.imag(Y_eq)>0)
41.
            BER[snr] = BER[snr] + np.sum(X_decI!=bitsI) + np.sum(X_decQ!=bitsQ)
43. BER = BER/N/2/nBlocks
44. SNR_eff = (L*SNR)/N
45. BERt = 0.5*(1-np.sqrt(SNR_eff/(2+SNR_eff)))
46.
47. plt.yscale('log')
48. plt.plot(SNRdB, BER, 'r-', SNRdB, BERt, 'b*')
49. plt.grid(1)
50. plt.suptitle('BER vs SNR curve for OFDM system')
51. plt.xlabel('SNR(dB)')
52. plt.ylabel('BER')
53. plt.legend(['Emperical', 'Analytical'])
```

Output Plot:

BER vs SNR curve for OFDM system



Inference:

For an N Subcarrier OFDM system and L i.i.d. Rayleigh Fading Channel Taps of Unit Gain, we get effective SNR as: $SNR_{eff} = \frac{L}{N}SNR$

And BER for an OFDM System is given by: $BER = \frac{1}{2} \left(1 - \sqrt{\frac{SNR_{eff}}{2 + SNR_{eff}}} \right)$

And BER for a SISO-OFDM System is given by: $BER_{SISO} = \frac{1}{2} \left(1 - \sqrt{\frac{\frac{LP}{NN_0}}{2 + \frac{LP}{NN_0}}} \right)$

Above is Theoretical BER, and after superposing it with or Analytical BER from Simulated OFDM System in Python, We Found it is almost same with some minor deviations from calculated values.