

# Design of QAM Receivers and SER Analysis

## Experiment - 5

### 1 Aim

To design a discrete time QAM communication receiver, and analyze the SER performance.

### 2 Theory

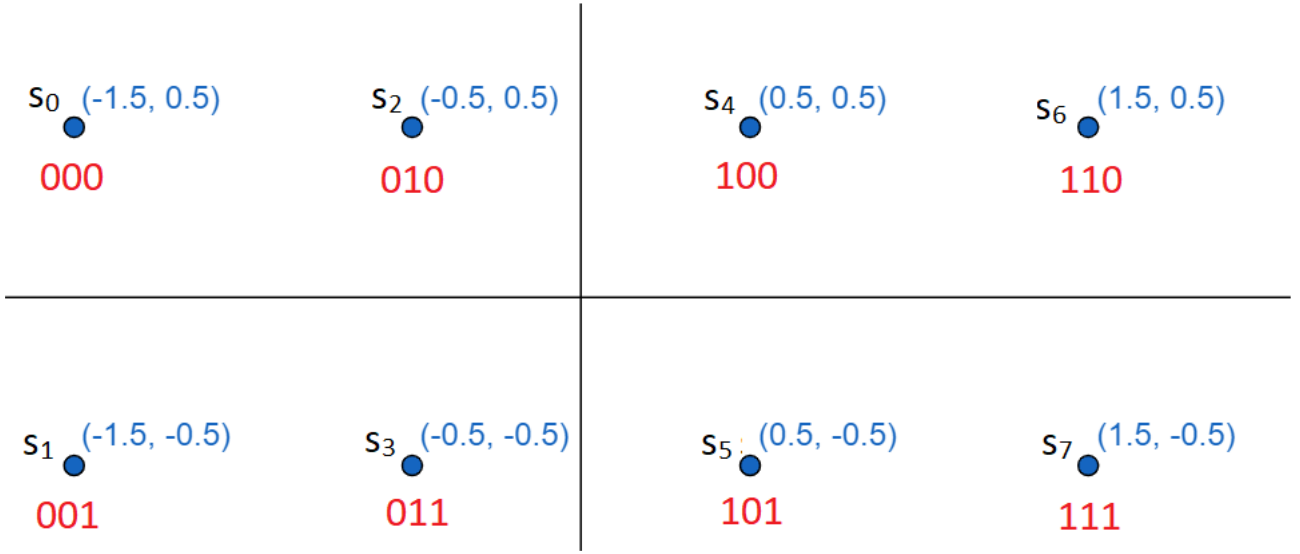


Fig.1 Constellation Map

#### 2.1 ML Rule

Since every symbol is equally likely, the ML rule is based on the shortest euclidean distance:

$$\arg \min ||y - s_i||^2, i = 0, 1, 2, \dots, 7$$

#### 2.2 SER

Let  $d$  be the distance between the points and  $E$  be the error bit. Let  $s_i$  be the  $i^{th}$  symbol and since all symbols are equally likely:

$$P(E = 1) = \sum_{i=1}^7 P(s_i)P(E | s_i) = \frac{1}{8} \sum_{i=1}^7 P(E | s_i) \quad (1)$$

Owing to the symmetry of the constellation, we can write:

$$\begin{aligned} P(E | s_0) &= P(E | s_1) = P(E | s_6) = P(E | s_7) \\ P(E | s_2) &= P(E | s_3) = P(E | s_4) = P(E | s_5) \end{aligned} \quad (2)$$

Thus, (1) reduces to:

$$P(E = 1) = \frac{P(E | s_1) + P(E | s_3)}{2} \quad (3)$$

Let  $S_k = [S_{1k}, S_{2k}]$  represent the symbol transmitted and  $N_k = [N_{1k}, N_{2k}]$  be the noise introduced by the AWGN channel such that  $Y_k = [Y_{1k}, Y_{2k}] = N_k + S_k$ . Then,

$$\begin{aligned} P(E | s_1) &= P(\{Y_{1k} > -d\} \cap \{P(Y_{2k} > 0)\}) \\ &= 1 - P(\{Y_{1k} < -d\} \cap \{P(Y_{2k} < 0)\}) \\ &= 1 - P(Y_{1k} < -d)P(Y_{2k} < 0) \end{aligned}$$

$$\begin{aligned}
&= 1 - P(S_{1k} + N_{1k} < -d)P(S_{2k} + N_{2k} < 0) \\
&= 1 - P(N_{1k} - 3d/2 < -d)P(N_{2k} - d/2 < 0) \\
&= 1 - P(N_{1k} < d/2)P(N_{2k} < d/2) \\
&= 1 - (1 - P(N_{1k} > d/2))^2 \\
&= 1 - \left(1 - P\left(\frac{N_{1k}}{\sigma} > \frac{d}{2\sigma}\right)\right)^2 \\
&= 1 - \left(1 - Q\left(\frac{d}{2\sigma}\right)\right)^2 \\
&= 2Q\left(\frac{d}{2\sigma}\right) - Q^2\left(\frac{d}{2\sigma}\right)
\end{aligned} \tag{4}$$

Similarly,

$$\begin{aligned}
P(E \mid s_3) &= P(\{Y_{1k} < -d, Y_{1k} > 0\} \cap \{P(Y_{2k} > 0)\}) \\
&= 1 - P(\{-d < Y_{1k} < 0\} \cap \{P(Y_{2k} < 0)\}) \\
&= 1 - P(-d < Y_{1k} < 0)P(Y_{2k} < 0) \\
&= 1 - P(-d < S_{1k} + N_{1k} < 0)P(S_{2k} + N_{2k} < 0) \\
&= 1 - P(-d < N_{1k} - d/2 < 0)P(N_{2k} - d/2 < 0) \\
&= 1 - P(-d/2 < N_{1k} < d/2)P(N_{2k} < d/2) \\
&= 1 - P\left(-\frac{d}{2\sigma} < N_{1k} < \frac{d}{2\sigma}\right)P\left(\frac{N_{2k}}{\sigma} < \frac{d}{2\sigma}\right) \\
&= 1 - P\left(-\frac{d}{2\sigma} < N_{1k} < \frac{d}{2\sigma}\right)P\left(\frac{N_{2k}}{\sigma} < \frac{d}{2\sigma}\right) \\
&= 1 - \left(1 - P\left(\frac{d}{2\sigma} > N_{1k} > -\frac{d}{2\sigma}\right)\right)\left(1 - P\left(\frac{N_{2k}}{\sigma} > \frac{d}{2\sigma}\right)\right) \\
&= 1 - \left(1 - 2Q\left(\frac{d}{2\sigma}\right)\right)\left(1 - Q\left(\frac{d}{2\sigma}\right)\right) \\
&= 3Q\left(\frac{d}{2\sigma}\right) - 2Q^2\left(\frac{d}{2\sigma}\right)
\end{aligned} \tag{5}$$

Substituting (4) and (5) in (3):

$$\boxed{P(E = 1) = 2.5Q\left(\frac{d}{2\sigma}\right) - 1.5Q^2\left(\frac{d}{2\sigma}\right)} \tag{6}$$

The average symbol energy can be found from the constellation map as:

$$\begin{aligned}
E_s &= \sum_k P(s_k) |s_k|^2 = \frac{4\left(\frac{d^2}{4} + \frac{d^2}{4}\right) + 4\left(\frac{9d^2}{4} + \frac{d^2}{4}\right)}{8} \\
E_s &= \frac{3d^2}{2}
\end{aligned} \tag{7}$$

Substituting (7) in (6):

$$\boxed{P_e = P(E = 1) = 2.5Q\left(\sqrt{\frac{E_s}{3N_0}}\right) - 1.5Q^2\left(\sqrt{\frac{E_s}{3N_0}}\right)} \tag{8}$$

### 3 Design

Input: NO\_OF\_BITS, EB\_N0\_DB, d  
Output: SER

```

M = 8
RIGHT = d / 2 + (M / 4 - 1) * d

```

```

LEFT = -RIGHT
constellation = [(±d/2 ± i*d, ±d/2)], i = 0, 1

map(symbol) = constellation[bin2dec(symbol)]
ML(Y) = argmin euclidean_distance(Y, constellation)

Sk = map(Bk.group(3))

for EB_N0 in EB_N0_DB
  Nk = AWGN(EB_N0, 2D)
  Yk = Sk + Nk
  sHat = dec2bin(ML(Yk))
  unchangedSymbols = count(sHat === Sk)
  SER = 1 - (unchangedSymbols/NO_OF_BITS)

plot(SER, SER_THEORETICAL)

```

The time complexity of the algorithm is  $O(N^2)$ .

## 4 JavaScript Code

### QAM.js

```

import DomHelpers from '../helpers/DomHelpers.js';
import SimulationHelpers from '../helpers/SimulationHelpers.js';

const S = new SimulationHelpers();
const D = new DomHelpers();

export default function QAM(d, SB_N0_DB, NO_OF_BITS) {
  const NO_OF_SYMBOLS = NO_OF_BITS / 3;
  const M = 8;
  const RIGHT = d / 2 + (M / 4 - 1) * d;
  const LEFT = -RIGHT;
  const Es = 1.5 * (d ** 2);
  const SER = new Array(SB_N0_DB.length);
  const SER_THEORETICAL = S.getTheoreticalSerQam8(SB_N0_DB, Es);
  const constellation = S
    .linspace(LEFT, RIGHT, d)
    .map((point) => [[point, d / 2], [point, -d / 2]])
    .flat();
  const Bk = S.randi([0, 1], NO_OF_BITS); // message
  const Sk = Bk.reduce((acc, bit, i) => { // modulation
    if (i % 3 === 0) {
      const tribit = [bit];
      acc.push(tribit);
    } else {
      acc[acc.length - 1].push(bit);
    }
    return acc;
  }, []).map((tribit) => constellation[parseInt(tribit.join(''), 2)]);
  for (let i = 0; i < SB_N0_DB.length; i += 1) {
    const Nk = S.getAWGN(SB_N0_DB[i], [NO_OF_SYMBOLS, 2]); // AWGN noise
    const Yk = new Array(NO_OF_SYMBOLS).fill(0).map((_, j) => S.sum(Sk[j], Nk[j]));
    const sHat = Yk.map(([x1, y1]) => {
      let shortestDistance = Infinity;
      let closestPoint;
      constellation.forEach(([x2, y2]) => {
        const distance = Math.hypot(x2 - x1, y2 - y1);
        if (distance < shortestDistance) {
          shortestDistance = distance;
          closestPoint = [x2, y2];
        }
      });
    });
    return S.dec2bin(D.indexOf(constellation, closestPoint), 3).split('').map((char) => Number(char));
  }
}

```

```

});
const unchangedSymbols = sHat.reduce((acc, symbol, j) => {
  const s = Bk.slice(3 * j, 3 * j + 3);
  // eslint-disable-next-line no-param-reassign
  if (symbol.toString() === s.toString()) acc += 1;
  return acc;
}, 0);
SER[i] = 1 - (unchangedSymbols / NO_OF_SYMBOLS);
}
return [SER, SER_THEORETICAL];
}

```

## SimulationHelpers.js

```

const { jStat } = window;

export default class SimulationHelpers {
  constructor() {
    this.sum = (arr1, arr2) => arr1.map((num, i) => num + arr2[i]);

    this.linspace = (start, stop, diff) => {
      const entries = [];
      let entry = start;
      while (entry <= stop) {
        entries.push(entry);
        entry += diff;
      }
      return entries;
    };

    this.qfunc = (arg) => 0.5 * jStat.erfc(arg / Math.SQRT2);

    this.getTheoreticalBerBpsk = (EB_N0_DB) => EB_N0_DB
      .map((EB_N0) => this.qfunc(Math.sqrt(2 * (10 ** (EB_N0 / 10)))));

    this.getTheoreticalSerQpsk = (SB_N0_DB) => SB_N0_DB
      .map((SB_N0) => 2 * this.qfunc(Math.sqrt(10 ** (SB_N0 / 10)))
        - this.qfunc(Math.sqrt(10 ** (SB_N0 / 10))) ** 2);

    this.getTheoreticalBerBfsk = (EB_N0_DB) => EB_N0_DB
      .map((EB_N0) => this.qfunc(Math.sqrt(10 ** (EB_N0 / 10))));

    this.getTheoreticalSerQam8 = (SB_N0_DB, Es) => SB_N0_DB
      .map((SB_N0) => 2.5 * this.qfunc(Math.sqrt(((10 ** (SB_N0 / 10)) * Es) / 3))
        - 1.5 * (this.qfunc(Math.sqrt(((10 ** (SB_N0 / 10)) * Es) / 3))) ** 2);

    this.getTheoreticalSerMpsk = (SB_N0_DB, M) => SB_N0_DB
      .map((SB_N0) => 2 * this
        .qfunc(Math.sqrt(2 * 10 ** (SB_N0 / 10)) * Math.sin(Math.PI / M)));

    this.randi = ([min, max], count) => {
      const integers = [];
      // eslint-disable-next-line no-plusplus, no-param-reassign
      while (count--) {
        integers.push(Math.floor(min + ((max - min + 1) * Math.random())));
      }
      return integers;
    };

    this.randn = (count) => new Array(count).fill(0).map(() => jStat.normal.sample(0, 1));

    this.getAWGN = (SB_N0_DB, [rows, cols]) => {
      const awgn = this.randn(rows * cols)
        .map((N) => N / Math.sqrt(2 * (10 ** (SB_N0_DB / 10))));
      if (cols === 1) return awgn;
      return awgn.reduce((acc, N, j) => {
        if (j % cols === 0) {

```

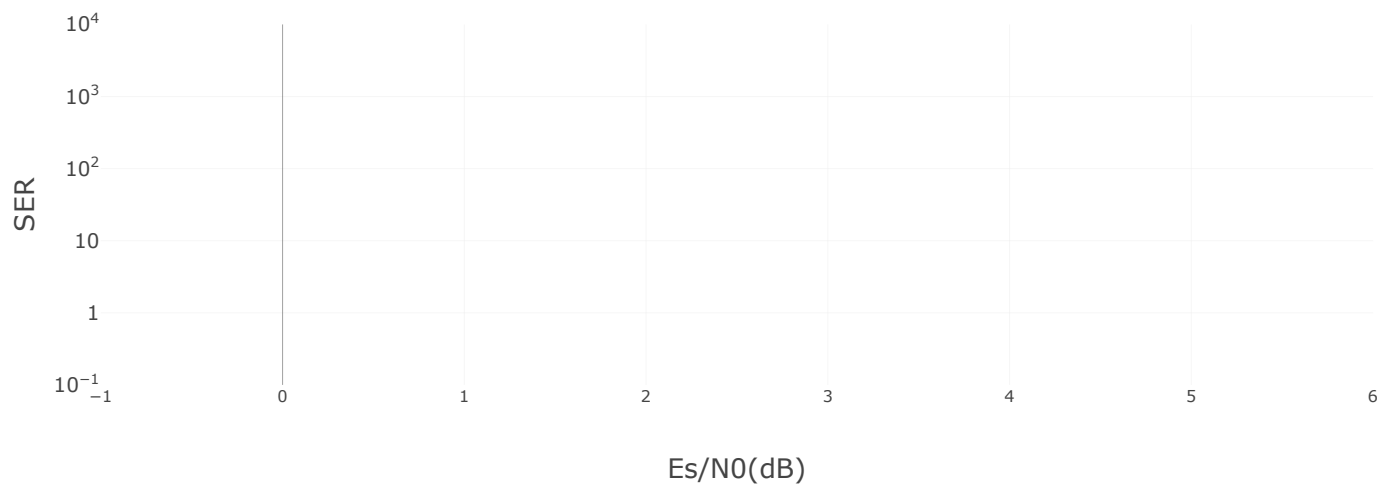
```

        const noise = [N];
        acc.push(noise);
    } else {
        acc[acc.length - 1].push(N);
    }
    return acc;
}, []);
};

this.dec2bin = (number, length) => {
    let binaryString = '';
    for (let i = 0; i < length - 1; i += 1) binaryString += '0';
    binaryString += number.toString(2);
    return binaryString.slice(-length);
};
}
}

```

## 5 Results and Inferences





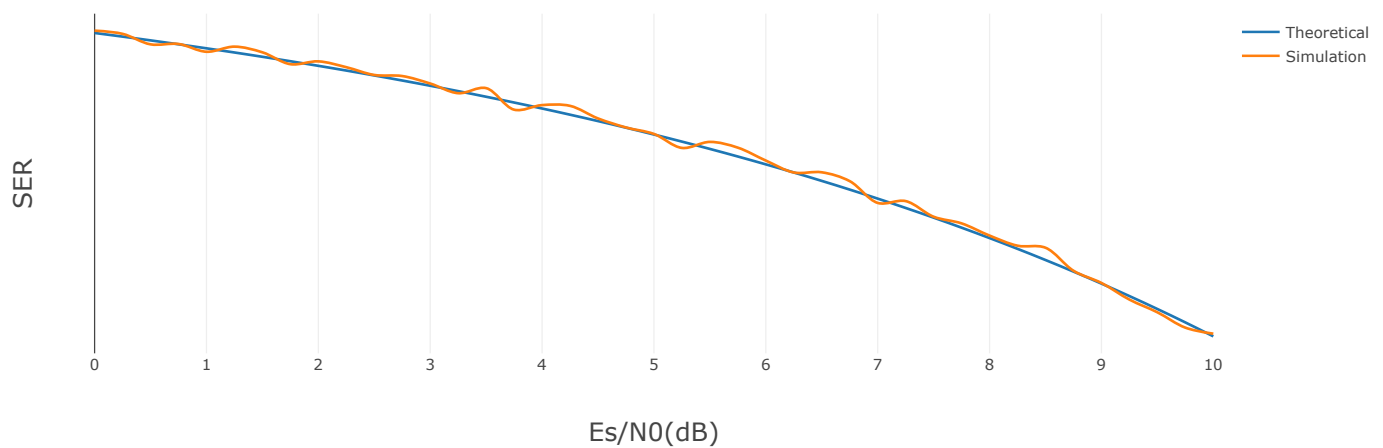



Fig.2 Simulation result for  $d = 0.1$  with  $3 \times 10^5$  bits

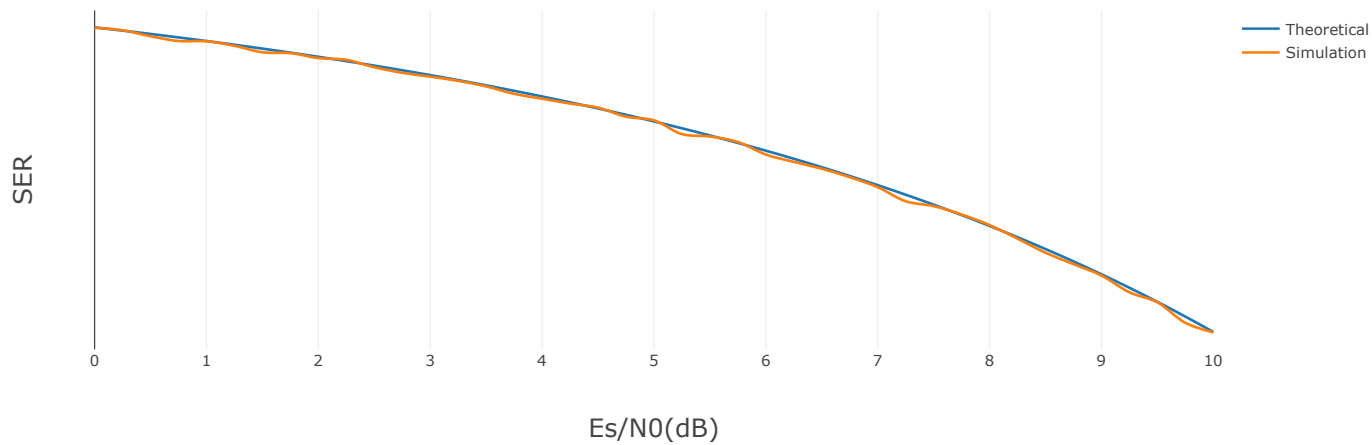


Fig.3 Simulation result for  $d = 0.25$  with  $3 \times 10^5$  bits

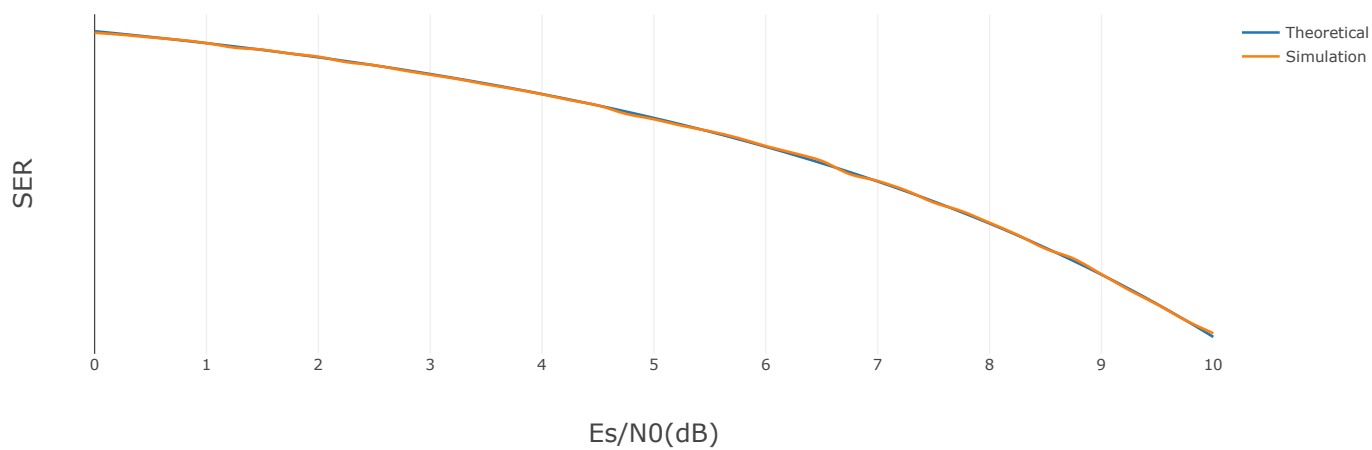


Fig.4 Simulation result for  $d = 0.5$  with  $3 \times 10^5$  bits

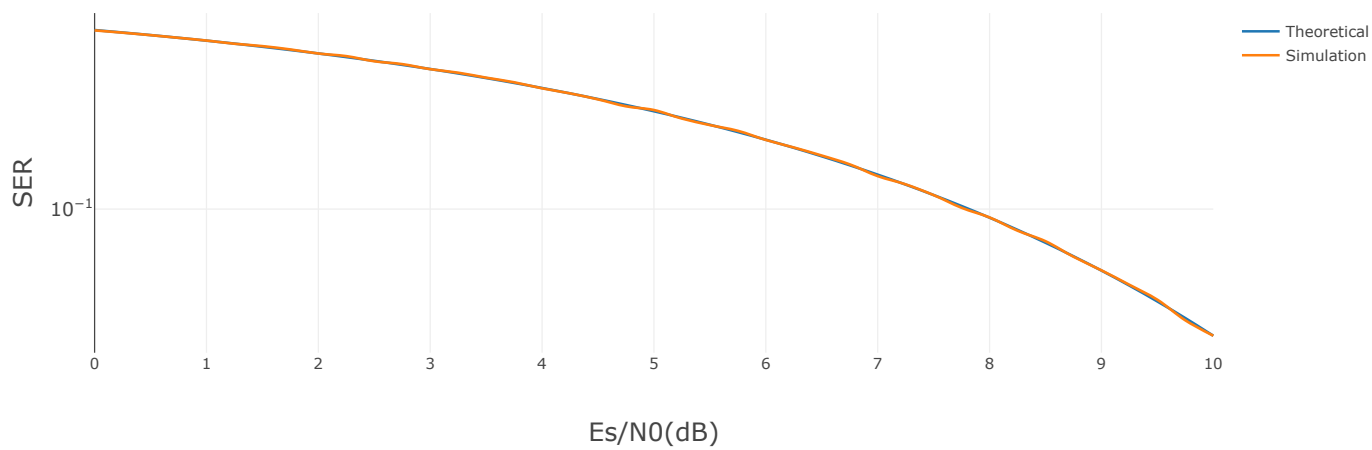


Fig.5 Simulation result for  $d = 1$  with  $3 \times 10^5$  bits

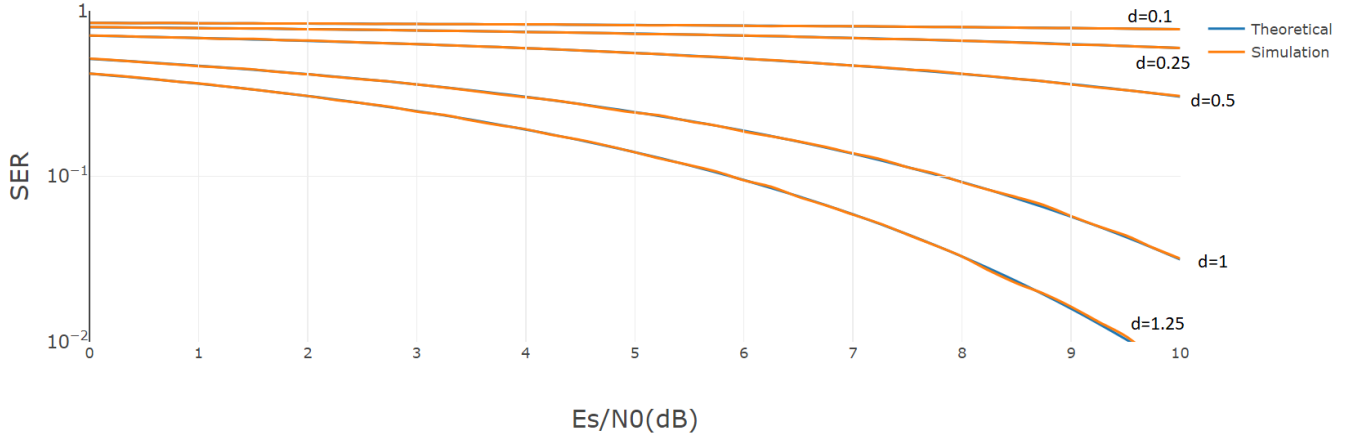


Fig.6 Comparison of simulation results for  $d = 0.1, 0.25, 0.5, 1$

From the above figures, it can be seen that for a given  $d$ , the simulated  $P_e$  and theoretical  $P_e$  match better with increase in the number of bits. This is because, to get confidence in the simulated results, there must be sufficient number of bit errors. For example, to get a bit error rate of  $10^{-5}$ , one needs to send at least  $10^6$  bits. Also, it can be seen that the  $P_e$  reduces gradually with increase in  $\frac{E_s}{N_0}$ , the SNR per symbol. This is due to the fact that as the SNR per symbol increases, the signal becomes less affected by the presence of noise, thus reducing errors in ML detection. Finally, another important thing to be noted is that the simulated curve is not only affected by the symbol errors, but is also affected by floating point errors.

From figure 6, we can see that the waterfall curve tends to flatten with decrease in  $d$ . This is because, with decrease in  $d$  the decision region becomes smaller and hence vastly increases the chances of symbol error. This also explains the fact that for larger  $d$ , the curves start from a lower SER closer to 0 and as  $D \rightarrow \infty$ ,  $SER \rightarrow 0$ .