School of Engineering and Applied Science (SEAS), Ahmedabad University

B.Tech(ICT) Semester V: Wireless Communication (CSE 311)

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- **Base Article Title :**

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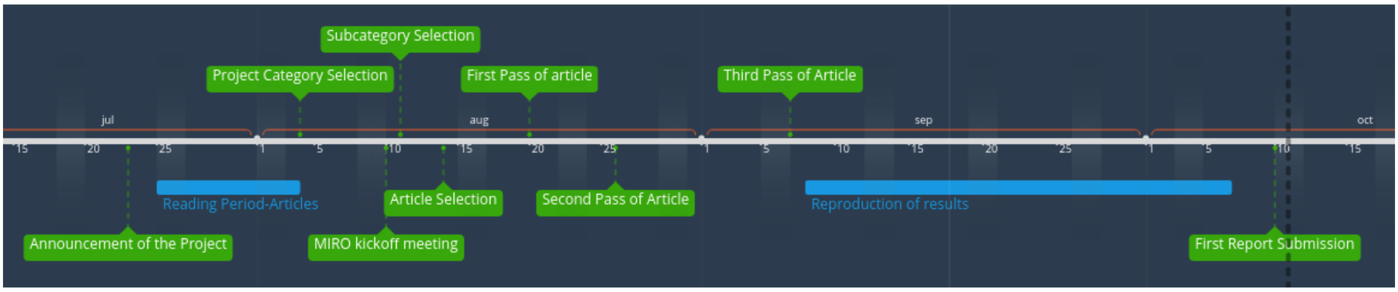
Timeline



1 Introduction

Molecular Communication is the transmission of information via propagation of the molecules *(information particles)* through the environment. In the communication of nano-devices, molecular communication becomes a more suitable option for applying the transmission techniques, as compared to the electromagnetic communication. Thus, it is an effective and energy-efficient method for transporting information.

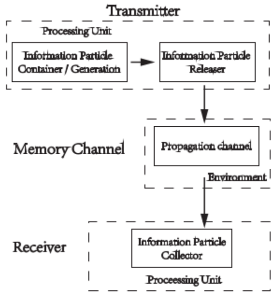


Figure 1: Block Diagram of Typical MC system

As shown in Fig-1, MC mainly comprises of five processes : encoding, emission *(transmission)*, propagation, absorption *(reception)* and decoding.

In this Communication the propagation takes place through diffusion and the modulation scheme used is known as Concentration Shift Keying *(CSK)* in which the encoding of information is done on the basis of the number of released particles. A point-like transmitter transmits the information particles which diffuse by Brownian motion *(motion random and independent of each other)* and then reach the receiver. Due to the intrinsic characteristics of diffusion, all the particles are not able to reach the receiver in the considered time-slot, and they reach in subsequent time-slots. This causes Inter-Symbol Interference (ISI), which if neglected, can degrade the system performance. So, it is important to consider ISI along with the background noise while optimizing the MC system.[1]-[5] The demodulation scheme for the binary symbol in MC system can be proposed as such:

$$Symbol\ detected = \begin{cases} 0 & ;\text{ if } r_i < \tau \\ \\ 1 & ;\text{ otherwise} \end{cases} \tag{1}$$

The approach proposed in this article calculates the BER of many threshold based detection schemes while considering the background noise and the ISI. The detection threshold is decided on the basis of the number of particles received in the previous time slot. The receiver structures proposed here have Zero-bit, One-bit and K-bit prior knowledge. So, we can apply this approach to receivers using any arbitrary number of past bits for detection. Here, this article also includes the comparison among these types of Receivers and conclude which of these will be more efficient for transmission.

Here, modeling, analysis and optimization of receiver schemes based on both, conventional detection theory as well as the data driven optimization approach using ANN have been developed.

The modeling and optimizing of the system model can get really complex. So, we can use the Machine Learning methods which do not rely on the knowledge of the system model and the channel. These methods can help in auto learning the whole system from the empirical data and there is no need for complex channel estimation or data equalization techniques for the data detection.

The machine learning approach uses the feed forward ANN's(Artificial Neural Networks) with fully connected layers. An observation has been made that the ANN's, without any prior knowledge of the system model show the same results as the conventional detection methods that depend on the perfect knowledge of the system model.

2 Assumptions

- The transmitter is considered as a point.
- The Receiver is considered as a spherical absorbing-type system
- The diffusion of the information particles through the medium is independent and random, so extra energy is not required.
- During the whole transmission, the temperature and viscosity are assumed to remain constant.
- Released time of Information particles from the transmitter is considered to be negligible.
- For tractability, it is assumed that C_i for i>L is negligible, so can be ignored in the background noise.
  C_i: Average received particles at the j^{th} time slot
  L: Length of the Poisson channel
- The Estimation of Information bits based on the received number of particles are assumed to be have equal probability.
- While computing the optimal threshold for the i^{th} time slot, the transmitted symbol s_{i-1} is assumed to be known. In practice, only its estimates can be obtained.

3 Performance Analysis of Base Article

- **System Model/Network Model :**

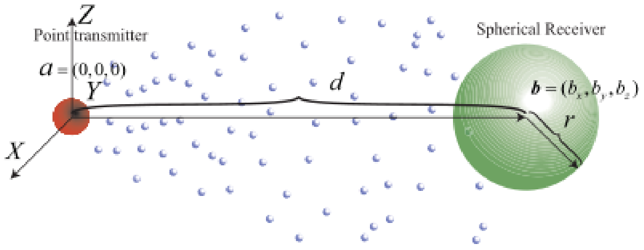


Figure 2: 3D unbounded molecular channel System Model

- **Channel Model**: 3-D unbounded diffusion channel without flow, point transmitter, spherical absorbing receiver[7][8].

- **Transmitted Signal**: Information particles, On-Off Modulation keying (OOK)

- **Nature of Noise**: ISI and background noise

- **List of symbols and their description :**

Symbol	**Description**
λ_0	Background noise power per unit time
r	Receiver Radius
d	Distance between transmitter and radius of receiver
D	Diffusion coefficient
ΔT	Discrete Time length
T	Slot Length
L	Channel Length

- **Detailed derivation of performance metric-I**:

  Let us consider s_i as the symbol to be transmitted. So the number of particles transmitted depends on whether 0 or 1 is to be transmitted.

$$S_i = \begin{cases} 1 & \text{, Then } N_{TX} \text{ particles are transmitted.} \\ 0 & \text{, Then no particles are transmitted} \end{cases} \tag{2}$$

  Now, as the diffusion process is slow the particles reach at different instances of the time. This causes ISI (intersymbol interference). Thus, the hitting rate of each particle is given by[6][8]

$$f_{hit}^{3D}(t) = \frac{r(d-r)e^{-\frac{(u-r)^2}{4Dt}}}{d\sqrt{4\pi Dt^3}} \tag{3}$$

where d= distance between T_x and R_x

r = diameter/2 = radius of the spherical receiver

D = Diffusion constant

The hitting probability of absorbing receiver in a given time slot is given by integration of PDF in above function in the form of error function.

$$P_{hit}(t) = \int_0^t f_{hit}(t)dt$$

$$P_{hit}(t) = \frac{r}{d} erfc\left(\frac{d-r}{\sqrt{4Dt}}\right) \tag{4}$$

So, the probability that one particle hits R_x at the $(i-1)$ th time slot is given by the integration of the PDF from (i-1)T to iT .

$$P_{i-1} = \int_{(i-1)T}^{iT} f_{hit}(t)dt$$

$$P_{i-1} = \frac{r}{d} erfc\left(\frac{d-r}{\sqrt{4DiT}}\right) - \frac{r}{d} erfc\left(\frac{d-r}{\sqrt{4D(i-1)T}}\right) \tag{5}$$

Now let C_j be the average number of particles received at the j th time slot. then

where $N_T x$ is the number of particles released

The received particles r_i seems to follow Poisson distribution.

$$\begin{gathered} r_i \sim \text{Poisson}\left(I_i + s_i C_0\right) \\ I_i = \lambda_0 T + \textstyle\sum_{j-1}^{L} C_j s_{i-j} \end{gathered} \tag{6}$$

I_i is the noise part in the signal considering the background noise and ISI.

$\therefore$ The probability of receiving r_i particles is

$$P\left(r_i \mid I_i + s_i C_0\right) = \frac{e^{-(I_i + s_i C_0)} \left(I_i + s_i C_0\right)^{r_i}}{r_i!} \tag{7}$$

The SNR is given by

$$SNR = 10 \log_{10} \left(\frac{C_0}{2\lambda_0 T} \right) \tag{8}$$

where c_o denotes the signal part and $\lambda_o T$ denotes background noise.

Putting the value of C_0 in equation (6)

$$N_{TX} = \frac{2\lambda_0 T (10)^{\frac{SNR}{10}}}{P_0} \tag{9}$$

This gives the number of particles released from Transmitter T_x

Optimal Zero Bit Memory Receiver

$\bar{s}_i$ denotes estimated symbol for the transmitted symbol s_i at i^{th} time slot.

Demodulation rule:

$$\overline{s_i} = \begin{cases} 0 & \text{if } r_i < \tau \\ 1 & \text{if } r_i \geq \tau \end{cases} \tag{10}$$

Also, from equation (7) and we have

$$P_{app}\left(r_i \mid s_i\right) = \frac{e^{-\lambda|_{s_i}} \left(\lambda|_{s_i}\right)^{r_i}}{r_i!}$$

$$\lambda|_{s_i} = \lambda_0 T + C_0 s_i + \frac{\sum_{j=1}^{L} C_j}{2}$$

Now, from above equations, the τ is obtained by $P\left(r_i = \tau \mid s_i = 0\right) = P\left(r_i = \tau \mid s_i = 1\right)$

$$\frac{e^{-\lambda|_{s_i=0}} (\lambda|_{s_i=0})^{r_i}}{r_i!} = \frac{e^{-\lambda|_{s_i=1}} (\lambda|_{s_i=1})^{ri}}{r_i!} \tag{11}$$

Thus, suboptimal threshold is given by

$$\tau = \frac{C_0}{\ln\left(1 + \left(\frac{C_0}{\left(\sum_{i=1}^{L} \frac{C_i}{2}\right) + \lambda_0 T}\right)\right)} \tag{12}$$

The optimal threshold that minimizes the BER of the zero-bit memory receiver is as follows:

$$(\tau^*, P_e^*) = \underset{\tau}{\arg\min} \quad P_e(\tau) \tag{13}$$

where $P_e(\tau)$ is the BFR as a function of τ :

$$P_e(\tau) = \frac{1}{2^L} \sum_{s_{l-1}} P_e\left(s_{i-1}, \tau\right) \tag{14}$$

and:

$$P_e\left(s_{i-1}, \tau\right) = \frac{1}{2}\left[Q\left(\lambda_0 T + \sum_{j=1}^{L} s_{i-j} C_j, \lceil \tau \rceil\right) + 1 - Q\left(\lambda_0 T + \sum_{j=1}^{L} s_{i-j} C_j + C_0, \lceil \tau \rceil\right)\right] \tag{15}$$

Proof: The BER is defined as follows:

$$P_e\left(s_{i-1}, \tau\right) = \frac{1}{2}\left[P\left(r_i \geq \tau \mid s_i = 0, s_{i-1}\right) + P\left(r_i < \tau \mid s_i = 1, s_{i-1}\right)\right] \tag{16}$$

where:

$$P\left(r_i \geq \tau \mid s_i = 0, s_{i-1}\right) = P\left(r_i \geq \tau \mid \lambda_0 T + \sum_{j=1}^{L} s_{i-j} C_j\right)$$

$$= \sum_{k=\lceil \tau \rceil} \frac{e^{-\left(\lambda_0 T + \sum_{j=1}^{L} s_{i-j} C_j\right)} \left(\lambda_0 T + \sum_{j=1}^{L} s_{i-j} C_j\right)^k}{k!}$$

$$\Longrightarrow P\left(r_i \geq \tau \mid s_i = 0, s_{i-1}\right) = Q\left(\lambda_0 T + \sum_{j=1}^{L} s_{i-j} C_j, \lceil \tau \rceil\right) \tag{17}$$

where:

$$P\left(r_i < \tau \mid s_i = 1, s_{i-1}\right) = P\left(r_i < \tau \mid \lambda_0 T + \sum_{j=0}^{L} s_{i-j} C_j\right)$$

$$= 1 - \sum_{k=\lceil \tau \rceil}^{\infty} \frac{e^{-\left(\lambda_0 T + \sum_{j=1}^{L} n_{-1} C_j + C_0\right)} \left(\lambda_0 T + \sum_{j=1}^{L} s_{i-j} C_j + C_0\right)^k}{k!}$$

$$P\left(r_i < \tau \mid s_i = 1, s_{i-1}\right) = 1 - Q\left(\lambda_0 T + \sum_{j=1}^{L} s_{i-j} C_j + C_0, \lceil \tau \rceil\right) \tag{18}$$

Thus, by substituting 17 and 18 in 16 we get,

$$P_e\left(s_{i-1},\tau\right)=\frac{1}{2}\left[Q\left(\lambda_0 T+\sum_{j=1}^{L}s_{i-j}C_j,\lceil\tau\rceil\right)\;+1-Q\left(\lambda_0 T+\sum_{j=1}^{L}s_{i-j}C_j+C_0,\lceil\tau\rceil\right)\right] \tag{19}$$

Optimal one bit receiver

The optimal detection threshold of the one-bit memory receiver can be formulated as follows:

$$\tau^*|_{s_{i-1}}=\arg\min_{\tau}\quad P_e\left(\tau,s_{i-1}\right) \tag{20}$$

where the BER is as follows:

$$P_e\left(\tau,s_{i-1}\right)=\frac{1}{2^{l,-1}}\sum_{x_{l-2},\cdots,s_{l-l}}P_e\left(s_{i-1},\tau\right) \tag{21}$$

since the exact symbol s_{i-1} is unknown, the estimates $\bar{s}_{i-1}$ are used to perform the detection:

$$\bar{s}_i=\begin{cases}0, & r_i\leq\tau|_{\bar{s}_{i-1}}\\ 1, & r_i>\tau|_{\bar{s}_{i-1}}\end{cases}$$

In order to compute the optimal threshold for the i th timeslot, the previously transmitted symbol s_{i-1} is assumed to be known. In practice, this is not possible, since only its estimates is available, as discussed already. Therefore, the BER needs to take this into account.
The BER of the one-bit memory detector can be formaldated as follows:

$$P_e=\frac{m+n}{2} \tag{22}$$

$$\begin{aligned} m=&\frac{1}{2^L}\sum_{s_{i-1}}\sum_{\bar{s}_{i-1}}Q\left(\lambda|_{s_{i-1},s_i=0},\lceil\tau_{|\bar{s}_{i-1}}\rceil\right)\times\Psi\left(s_{i-1},\bar{s}_{i-1},m,n\right)\\ n=&\frac{1}{2^L}\sum_{s_{i-1}}\sum_{\bar{s}_{i-1}}\left(1-Q\left(\lambda|_{s_{i-1},s_i=1},\lceil\tau_{|\bar{s}_{i-1}}\rceil\right)\right)\times\Psi\left(s_{i-1},\bar{s}_{i-1},m,n\right)\end{aligned}$$

where $\tau|_{\bar{s}_{i-1}}$ is the optimal threshold that corresponds to the previously detected bit s_{i-1}, $\lambda|_{s_{i-1,H}-0}$ is the average number of received particles by conditioning on the current symbol being 0 and the previous L symbols being s_{i-1}, $\sum_{j=1}^{L}C_j s_{i-j}+\lambda_0 T+C_0$ The function $\Psi\left(s_{i-1},\bar{s}_{i-1},m,n\right)$ is defined as follows:

$$\psi\left(s_{i-1},\bar{s}_{i-1},m,n\right)=\begin{cases} m & s_{i-1}=0,\bar{s}_{i-1}=1 \\ 1-m & s_{i-1}=0,\bar{s}_{i-1}=0 \\ n & s_{i-1}=1,\bar{s}_{i-1}=0 \\ 1-n & s_{i-1}=1,\bar{s}_{i-1}=1 \end{cases} \tag{23}$$

Optimal K-bit receiver

The optimal detection threshold of the K-bit memory receiver can be formulated as follows:

$$\tau^*|_{s_{i-1},\ldots,s_{i-K}} = \arg\min_{\tau} \quad P_e\left(\tau, s_{i-1},\ldots,s_{i-K}\right) \tag{24}$$

where the BER is as follows:

$$P_e\left(\tau, s_{i-1},\ldots,s_{i-K}\right)=\frac{1}{2^{L-K}}\sum_{s_{i-K+1},\cdots,s_{i-L}} P_e\left(s_{i-1},\tau\right)$$

since the exact symbols s_{i-j}, for $1 \leq j$ are unknown, the estimates $\bar{s}_{i-1},\ldots,\bar{s}_{i-K}$ are used to perform the detection:

$$\bar{s}_i=\begin{cases} 0, & r_i \leq \tau|_{\bar{s}_{i-1},\ldots,\bar{s}_{i-K}} \\ 1, & r_i > \tau|_{\bar{s}_{i-1},\ldots,\bar{s}_{i-K}} \end{cases}$$

The BER can predicted from Equation where :

$$m = \frac{1}{2^L}\sum_{s_{i-1}}\sum_{\bar{s}_{i-1},\ldots,\bar{s}_{i-K}} Q\left(\lambda|_{s_{i-1},s_i=0}, \lceil\tau \mid \bar{s}_{i-1},\ldots,\bar{s}_{i-K}\rceil\right)\times\prod_{j=1}^{K}\Psi\left(s_{i-j},\bar{s}_{i-j},m,n\right)$$

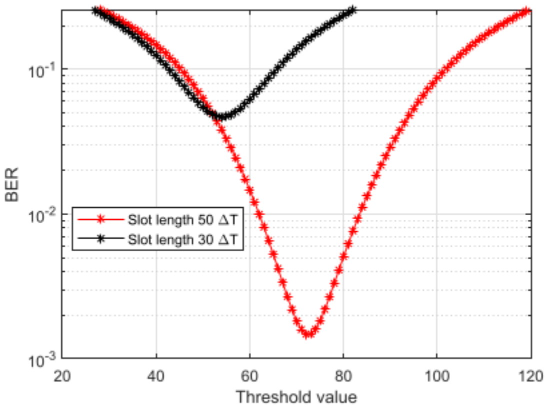
$$n = \frac{1}{2^L}\sum_{s_{i-1}}\sum_{\bar{s}_{i-1},\ldots,\bar{s}_{i-K}} \left(1-Q\left(\lambda|_{s_{i-1},s_i=1}, \lceil\tau \mid \bar{s}_{i-1},\ldots,\bar{s}_{i-K}]\right)\right)\times\prod_{j=1}^{K}\Psi\left(s_{i-j},\bar{s}_{i-j},m,n\right)$$

4 Numerical Results

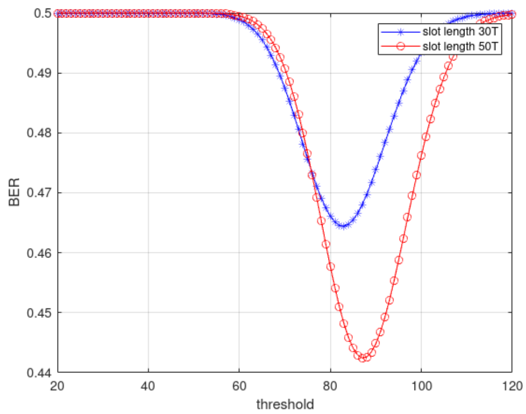
4.1 Reproduced Figures

- Reproduced Figure-1

  – Figures :



(a) 1-B



(b) 1-R

Figure 3: BER in (14) as a function of τ (the SNR is 30 dB)

  – Description :

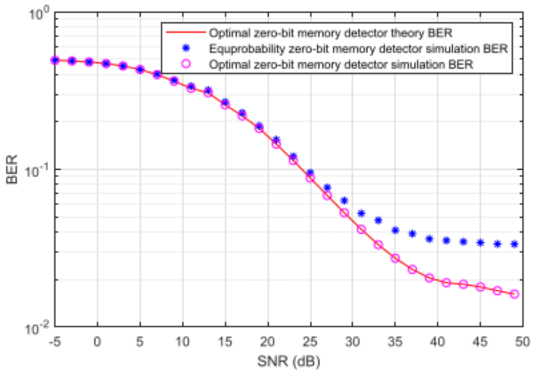
    * This figure describes the nature of B.E.R. of Zero-Bit Memory detector with respect to the different Sub-Optimal Thresholds.

  – Inferences :

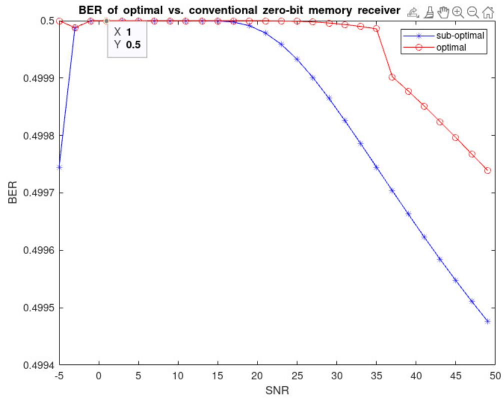
    * There exists a τ that minimizes the BER.
    * τ depends on the time slot duration T i.e. the amount of ISI.

- Reproduced Figure-2

  - Figures



(a) 2-B



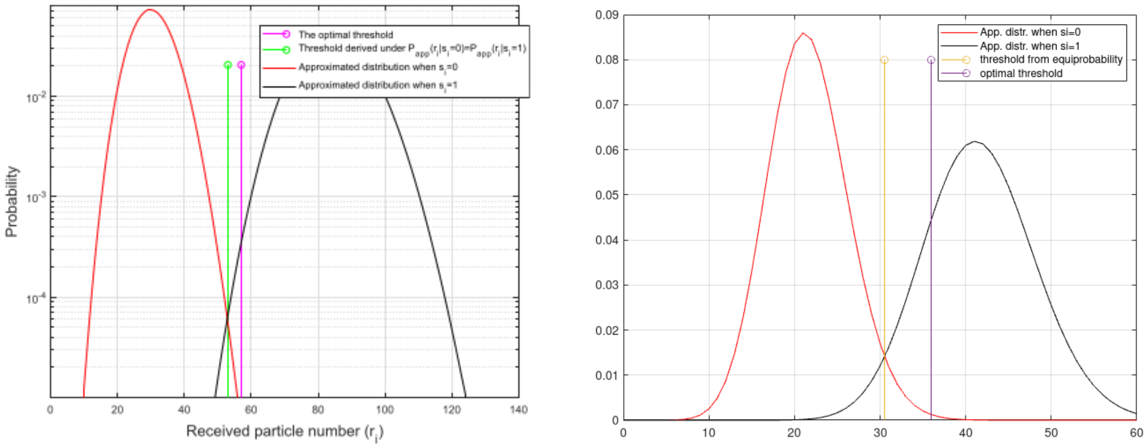
(b) 2-R

Figure 4: BER of optimal vs. conventional zero-bit memory receiver - T = 30ΔT .

  - Description : This figure describes the nature of BER of Zero-Bit Memory Receiver depending on Signal to Noise Ratio (SNR in dB).
  - Inferences :
    - At low value of SNR, the simulations for Equiprobable Zero-Bit Memory detector resembles Optimal Zero-Bit Memory detector
    - At Higher value of SNR, Equiprobable Zero-Bit Memory Detector performs better than Optimal based Detector
    - After some SNR value, the BER of both detectors becomes almost constant respectively.
    - The proposed analytical framework gives good accuracy.

- Reproduced Figure-3

  - Figures



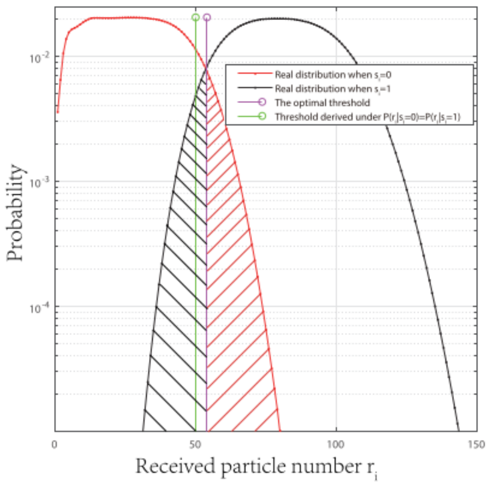
(a) 3-B (b) 3-R

Figure 5: Approximated distributions of the received bits from (11) (SNR = 25 dB).

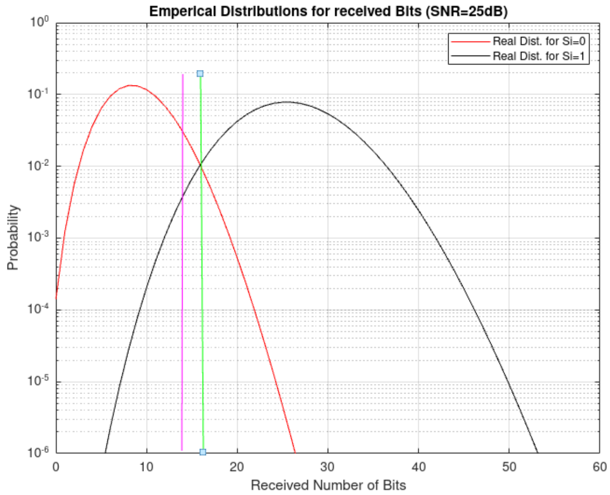
  - Description : This graph represents the approximated distributions of received bits based on the received number of particles. Here, The marker at the intersection of both distribution represents the sub-optimal threshold. Thus, if the number of received particles are greater than the Sub-Optimal threshold, the Bit received is estimated as 1 and 0 otherwise.

- Reproduced Figure-4

  - Figures



(a) 4-B



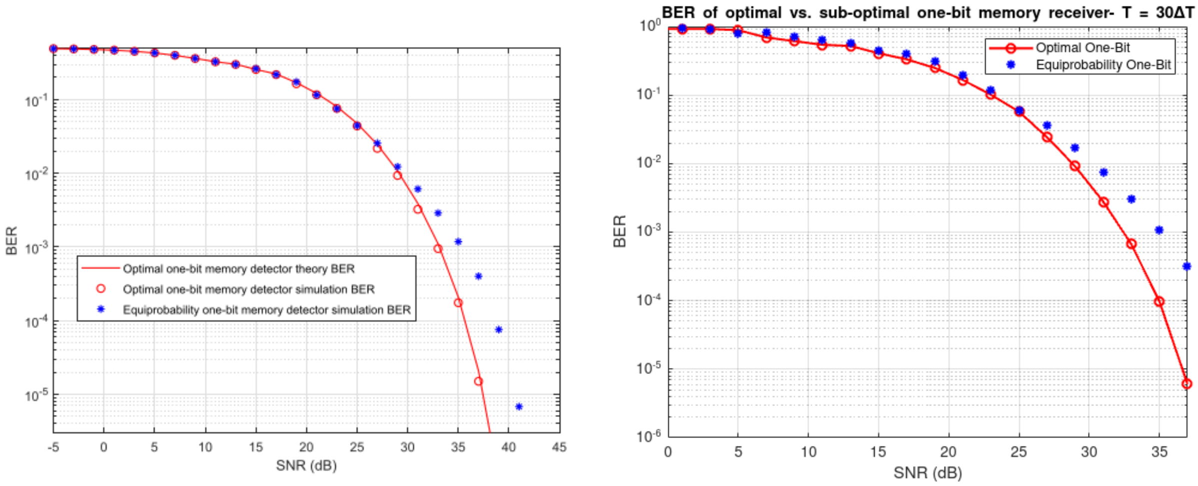
(b) 4-R

Figure 6: Empirical distributions of the received bits (SNR = 25 dB).

  - Description : This graph represents the empirical distribution of received bits based on the received number of particles. Here, The marker at the intersection of both distribution represents the optimal threshold. Thus, if the number of received particles are greater than the Optimal threshold, the Bit received is estimated as 1 and 0 otherwise.

- <u>Reproduced Figure-5</u>

  - Figures



(a) 5-B

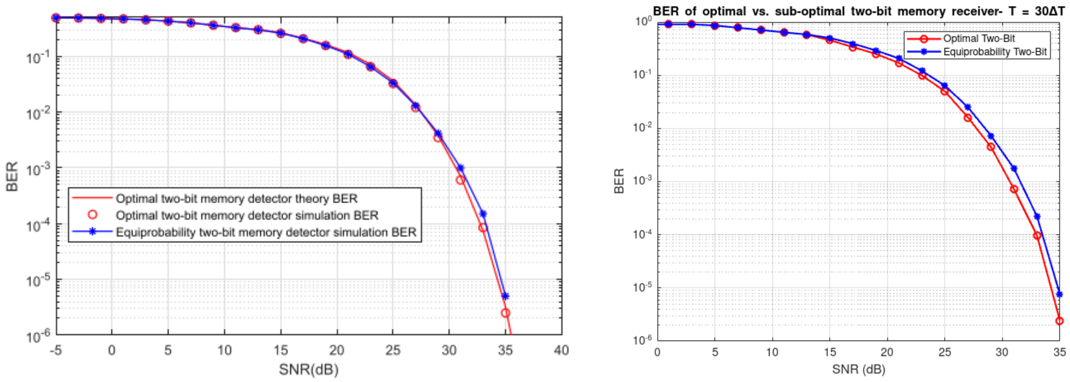
(b) 5-R

Figure 7: BER of optimal vs. sub-optimal one-bit memory receiver.

  - Description : This graph represents the nature of optimal and sub-optimal 1-Bit Memory Detectors at different SNR value.
  - Inferences:
    * Variations in BER are observed in the optimal and sub-optimal approach for 1-Bit memory detection at larger S.N.R. value which increases as SNR increases because the ISI is modelled accurately.
    * The variation is comparatively less than that observed in 0-Bit Memory Detectors.

- Reproduced Figure-6

  – Figures



(a) 6-B (b) 6-R

Figure 8: Two-bit memory detector: Comparison between the optimal and sub-optimal setups of the demodulation thresholds

  – Description : This graph represents the nature of optimal and sub-optimal 2-Bit Memory Detectors at different SNR value.

  – Inferences:

    * The optimal and sub-optimal approach for 2-Bit memory detection have very minute variations in B.E.R. at larger S.N.R. value

    * The variation is comparatively very less than that observed in 1-Bit and 0-Bit Memory Detectors

4.2 Conclusive Summary

- The more number of memory bits, the better the ISI is modeled. As the memory length approaches the channel length, thus, the optimal threshold converges towards the conventional threshold

- After some larger value of SNR, BER of zero bit Receiver becomes constant while BER of 1-bit and 2-Bit continue to decrease.

- As shown in Fig 3-B and 4-B, the empirical and the theoretical distributions of the received number of particles are different. Also, the distributions intersect at different thresholds (i.e. Empirical Distributions intersect at Optimal Threshold while Approximated Distributions meet at Sub-Optimal Threshold.)

5 Contribution of team members

5.1 Technical contribution of all team members

Enlist the technical contribution of members in the table. Redefine the tasks (e.g Task-1 as simualtion of fig.1 and so on)

Tasks	**Shaili Gandhi**	**Manav Vagrecha**	**Devam Shah**
Analysis	✓	✓	✓
Derivation	✓	-	✓
Coding	-	✓	-
Inference	✓	✓	✓

5.2 Non-Technical contribution of all team members

Enlist the non-technical contribution of members in the table. Redine the tasks (e.g Task-1 as report writing etc.)

Tasks	**Shaili Gandhi**	**Manav Vagrecha**	**Devam Shah**
Base Article Selection	✓	✓	✓
Concept Map	✓	✓	✓
MIRO	✓	✓	✓
Report	✓	✓	✓

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