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:

  X. Qian, M. D. Renzo, and A. Eckford, "Molecular Communications: Model-Based and Data-Driven Receiver Design and Optimization," IEEE Access, vol. 7, pp. 53555–53565, Apr. 2019. [1]

1 Performance Analysis of Base Article(Analytical Model)

1.1 List of symbols and their description:

Symbol	Description	value
λ_0	background noise power per unit time	$100s^{-1}$
r	Receiver radius	45 nm
d	Distance	500 nm
D	Diffusion coefficient	$4.265 * 10^{-10} m^2/s$
ΔT	Discrete time length	9 us
T	Slot length	$30\Delta T$
L	Channel length	5

1.2 System Model:

- **Channel model: Diffusion via Brownian Motion** based channel model
- **Transmitted signal:** The transmitted signal is in the form of **Information particles** (0 or 1) which are modulated using **On-Off Keying (OOK)** model.

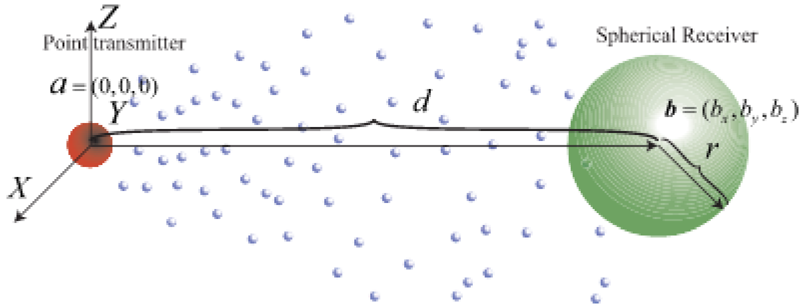


Figure 1: The 3D unbounded molecular channel model

- **Nature of noise:** The main noises involved in the model are **background noise** and **ISI**

The detailed explanation of the system model is as follows:

Here we have considered the OOK (On-Off Keying) approach [2] to check when the particles will be released, hence the value to s_i, the signal symbol, particles will be transmitted as:

- $s_i = 1$, N_{TX} particles will be transmitted
- $s_i = 0$, particles are not transmitted

Due to the random nature of the motion of these particles there is a high possibility that they will reach the receiver at different instances of time, hence the rate of a particle hitting the spherical receiver will be:

$$f_{hit}^{3D}(t) = \frac{r(d-r)e^{-\frac{(d-r)^2}{4Dt}}}{d\sqrt{4\pi Dt^3}} \tag{1}$$

where,

r = radius of the spherical receiver

d = distance between T_X and R_X

D = Diffusion constant

This random nature results in **ISI**, or **Inter-symbol Interference** between the particles. Now based on the hitting rate, $f_{hit}^{3D}(t)$, the Hitting Probability ($P_{hit}(t)$), for particles can be given by:

$$P_{hit}(t) = \int_0^t f_{hit}(t)dt = \frac{r}{d}erfc\left(\frac{d-r}{\sqrt{4Dt}}\right) \tag{2}$$

This is the cumulative probability for all the particles in time slot 0 to t, hence, probability of single particle hitting the receiver [3] is:

$$P_{i-1} = \frac{r}{d}erfc\left(\frac{d-r}{\sqrt{4Dit}}\right) - \frac{r}{d}erfc\left(\frac{d-r}{\sqrt{4D(i-1)t}}\right) \tag{3}$$

Now the number of particles released by the transmitter $= N_TX$, hence, the average number of particles that will be received in the j^{th} time slot, (C_j) will be given by:

$$C_j = N_{TX}P_j \tag{4}$$

Now the number of received particles, r_i follow a Poisson distribution, hence they can be given by:

$$r_i \sim Poisson(I_i + s_i C_0) \tag{5}$$

where,

I_i: sum of ISI and background noise, and is given by, $I_i = \lambda_0 T + \sum_{j=0}^{\infty} C_j s_{i-j}$ $\therefore$ Probability of receiving information particles r_i is:

$$P(r_i | I_i + s_i C_0) = \frac{e^{-(I_i + s_i C_0)}(I_i + s_i C_0)^{r_i}}{r_i!} \tag{6}$$

Now, to make calculations easier, we assume that C_j for all $i > L$ is small enough and can be considered as background noise and hence does not contribute to ISI. Hence, SNR can be given by:

$$SNR = 10 \log_{10}\left(\frac{C_0}{2\lambda_0 T}\right) \tag{7}$$

Hence, based on a given SNR, the number of released particles $N_T X$ can be given by:

$$N_{TX} = \frac{2\lambda_0 T 10^{(\frac{SNR}{10})}}{P_0} \tag{8}$$

1.3 Detailed derivation of performance metric-I

The first performance metric is **BER (Bit Error Probability) vs SNR** for the Zero-bit, One-bit and K-bit Memory receiver (analytical and data driven). [4]

- **Zero Bit Memory Receiver** Here, as the receiver is zero bit memory type, the demodulation depends on none of the previous symbol bits. [5]
  We consider,

$$\overline{s_i} = \begin{cases} 0 & r_i \leq \tau \\ 1 & r_i > \tau \end{cases} \tag{9}$$

  Here, BER $P_e(\tau)$,j=1 can be considered as a function of threshold as:

$$P_e(\tau) = \frac{1}{2^L} \sum_{s_{i-1}} P_e(s_{i-1}, \tau) \tag{10}$$

  and, $P_e(s_{i-1}, \tau)$ can be written as:

$$P_e(s_{i-1}, \tau) = \frac{1}{2}[Q(\lambda_0 T + \sum_{j=1}^{L} s_{i-j} C_j, \lceil \tau \rceil) + 1 - Q(\lambda_0 T + \sum_{j=1}^{L} s_{i-j} C_j + C_0, \lceil \tau \rceil)] \tag{11}$$

  hence, it is equal to:

$$P_e(s_{i-1}, \tau) = \frac{1}{2}[P(r_i \geq \tau | s_i = 0, s_{i-1}) + P(r_i < \tau | s_i = 1, s_{i-1})] \tag{12}$$

where, the probabilities can be expanded as:

$$P(r_i \geq \tau | s_i = 0, s_{i-1}) = P(r_i \geq \tau | \lambda_0 T + \sum_{j=1}^{L} s_{i-j} C_j) \tag{13}$$

It can be expressed as an expansion of Poisson random variable as:

$$P(r_i \geq \tau | s_i = 0, s_{i-1}) = \sum_{k=\lceil \tau \rceil}^{\infty} \frac{e^{-\left(\lambda_0 T + \sum_{j=1}^{L} s_{i-j} C_j\right)} \left(\lambda_0 T + \sum_{j=1}^{L} s_{i-j} C_j\right)^k}{k!} \tag{14}$$

which can be written in compact form as:

$$P(r_i \geq \tau | s_i = 0, s_{i-1}) = Q(\lambda_0 T + \sum_{j=1}^{L} s_{i-j} C_j, \lceil \tau \rceil) \tag{15}$$

Similarly, for $P(r_i < \tau | s_i = 1, s_{i-1})$, we can write:

$$\begin{aligned} P(r_i < \tau | s_i = 1, s_{i-1}) &= P(r_i < \tau | \lambda_0 T + \sum_{j=0}^{L} s_{i-j} C_j) \\ &= \sum_{k=0}^{\lceil \tau \rceil - 1} \frac{e^{-\left(\lambda_0 T + \sum_{j=1}^{L} s_{i-j} C_j + C_0\right)} \left(\lambda_0 T + \sum_{j=1}^{L} s_{i-j} C_j + C_0\right)^k}{k!} \\ &= 1 - \sum_{k=\lceil \tau \rceil}^{\infty} \frac{e^{-\left(\lambda_0 T + \sum_{j=1}^{L} s_{i-j} C_j\right)} \left(\lambda_0 T + \sum_{j=1}^{L} s_{i-j} C_j\right)^k}{k!} \\ &= 1 - Q(\lambda_0 T + \sum_{j=1}^{L} s_{i-j} C_j + C_0, \lceil \tau \rceil) \end{aligned} \tag{16}$$

Using equation (15) and (16), we can get the value of BER as given in equation (10).

- **One Bit Memory Receiver** Here, as the receiver is one bit memory type, the demodulation depends on one previous symbol bit. [5]

  We consider

$$\overline{s_i} = \begin{cases} 0 & r_i \leq \tau|_{s_{i-1}} \\ 1 & r_i > \tau|_{s_{i-1}} \end{cases} \tag{17}$$

  Here, the threshold value is considered to considered to be a function of the previously transmitted bit.So, the threshold changes in every time slot.

  Here, we have assumed that the previously transmitted bit is known to us.

  The optimal threshold can be calculated from:

$$\tau^*|_{s_{i-1}} = argminP_e(\tau, s_{i-1}) \tag{18}$$

  The BER equation can be calculated with the help of the parameters τ and s_{i-1} i.e. the previously transmitted bit.

$$P_e(\tau, s_{i-1}) = \frac{1}{2^{L-1}} \sum_{s_{i-2},\dots,s_{i-L}} P_e(s_{i-1}, \tau) \tag{19}$$

But in practical situations we assume that only estimated previously transmitted bit is available and so the BER is calculated with that value.

$$P_e(\tau, s_{i-1}) = \frac{1}{2}[P(\overline{s}_i = 1|s_i = 0) + P(\overline{s}_i = 0|s_i = 1)] \tag{20}$$

Here let us assume,

$$m = P(\overline{s}_i = 1|s_i = 0)$$
$$n = P(\overline{s}_i = 0|s_i = 1)$$

So,

$$P_e(\tau, s_{i-1}) = \frac{m+n}{2} \tag{21}$$

Calculating the value of m,

$$\begin{aligned} m &= P_e(\overline{s}_i = 1|s_i = 0) \\ &= \sum_{s_{i-1},\overline{s}_{i-1}} P(\overline{s}_i = 1|s_i = 0, s_{i-1}, \overline{s}_{i-1}) * P(\overline{s}_{i-1}, s_{i-1}, ..., s_{i-L}) \\ &= \sum_{s_{i-1},\overline{s}_{i-1}} P(r_i \geq \tau|s_i = 0, s_{i-1}, \overline{s}_{i-1}) * P(\overline{s}_{i-1}|s_{i-1})P(s_{i-1})P(s_{i-2}, ..., s_{i-L}) \\ &= \frac{1}{2^L} \sum_{s_{i-1},\overline{s}_{i-1}} P(\overline{s}_{i-1}|s_{i-1})Q(\lambda|_{s_{i-1},s_i=0}, \tau_{\overline{s}_{i-1}}) \end{aligned} \tag{22}$$

where $\lambda|_{s_{i-1},s_i=0} = \lambda_0 T + \sum_{j=1}^{L} s_{i-j}C_j$

Calculating the value of n,

$$\begin{aligned} n &= P_e(\overline{s}_i = 0|s_i = 1) \\ &= \sum_{s_{i-1},\overline{s}_{i-1}} P(\overline{s}_i = 0|s_i = 1, s_{i-1}, \overline{s}_{i-1}) * P(\overline{s}_{i-1}, s_{i-1}, ..., s_{i-L}) \\ &= \sum_{s_{i-1},\overline{s}_{i-1}} P(r_i < \tau|s_i = 1, s_{i-1}, \overline{s}_{i-1}) * P(\overline{s}_{i-1}|s_{i-1})P(s_{i-1})P(s_{i-2}, ..., s_{i-L}) \\ &= \frac{1}{2^L} \sum_{s_{i-1},\overline{s}_{i-1}} P(\overline{s}_{i-1}|s_{i-1})(1 - Q(\lambda|_{s_{i-1},s_i=1}, \tau_{\overline{s}_{i-1}})) \end{aligned} \tag{23}$$

where $\lambda|_{s_{i-1},s_i=1} = \lambda_0 T + \sum_{j=1}^{L} s_{i-j}C_j + C_0$

Putting equation (22) and (23) in equation (21) we get the value of BER.

Here, $P(\overline{s}_{i-1}|s_{i-1})$ can be replaced with the Ψ function which can be defined as follows.

$$\Psi(s_{i-1},\overline{s}_{i-1},m,n) = \begin{cases} m & s_{i-1}=0,\overline{s}_{i-1}=1 \\ 1-m & s_{i-1}=0,\overline{s}_{i-1}=0 \\ n & s_{i-1}=1,\overline{s}_{i-1}=0 \\ 1-n & s_{i-1}=1,\overline{s}_{i-1}=1 \end{cases} \tag{24}$$

So, m and n will be,

$$m = \frac{1}{2^L}\sum_{\overline{s}_{i-1}}\sum_{s_{i-1}} Q(\lambda|_{s_{i-1},s_i=0},\tau_{\overline{s}_{i-1}})\Psi(s_{i-1},\overline{s}_{i-1},m,n) \tag{25}$$

$$n = \frac{1}{2^L}\sum_{\overline{s}_{i-1}}\sum_{s_{i-1}} (1-Q(\lambda|_{s_{i-1},s_i=1},\tau_{\overline{s}_{i-1}}))\Psi(s_{i-1},\overline{s}_{i-1},m,n) \tag{26}$$

- **K Bit Memory Receiver** Here, as the receiver is k bit memory type, the demodulation depends on k previous symbol bits. [5]

  We consider

$$\overline{s_i} = \begin{cases} 0 & r_i \leq \tau|_{\overline{s}_{i-1},\ldots,\overline{s}_{i-k}} \\ 1 & r_i > \tau|_{\overline{s}_{i-1},\ldots,s_{i-k}} \end{cases} \tag{27}$$

Here, the threshold value is considered to considered to be a function of the k previously transmitted bit.So, the threshold changes in every time slot.

Here, we have assumed that all the k previously transmitted bits are known to us.

The optimal threshold can be calculated from:

$$\tau^*|_{s_{i-1},\ldots,s_{i-K}} = argmin P_e(\tau, s_{i-1},...,s_{i-K}) \tag{28}$$

The BER equation can be calculated with the help of the parameters τ and $s_{i-1},...,s_{i-K}$ i.e. the previously transmitted bit.

$$P_e(\tau, s_{i-1},...,s_{i-K}) = \frac{1}{2^{L-K}}\sum_{s_{i-K+1},\ldots,s_{i-L}} P_e(s_{i-1},\tau) \tag{29}$$

Since the exact symbol time is not known we use the estimates $\overline{s}_{i-1},...,\overline{s}_{i-K}$.

$$P_e(\tau, s_{i-1},...,s_{i-K}) = \frac{1}{2}[P(\overline{s}_i=1|s_i=0)+P(\overline{s}_i=0|s_i=1)] \tag{30}$$

Here let us assume,

$$m = P(\overline{s}_i = 1|s_i = 0)$$
$$n = P(\overline{s}_i = 0|s_i = 1)$$

So,

$$P_e(\tau, s_{i-1}, ..., s_{i-K}) = \frac{m+n}{2} \tag{31}$$

where

Calculating the value of m,

$$\begin{aligned}
P(\overline{s}_i = 1|s_i = 0) = &\sum_{s_{i-1},\overline{s}_{i-1},...,\overline{s}_{i-K}} P(\overline{s}_i = 1|s_i = 0, s_{i-1}, \overline{s}_{i-1}, ..., \overline{s}_{i-K}) * P(\overline{s}_{i-1}, s_{i-1}, ..., s_{i-K}) \\
= &\sum_{s_{i-1},\overline{s}_{i-1},...,\overline{s}_{i-K}} P(\overline{s}_i = 1|s_i = 0, s_{i-1}, \overline{s}_{i-1}, ..., \overline{s}_{i-K}) * P(\overline{s}_{i-1}|s_{i-1}, ..., s_{i-L}, \overline{s}_{i-2}, ..., \overline{s}_{i-K}) \\
&P(s_{i-1})P(s_{i-2}, ..., s_{i-L}, \overline{s}_{i-2}, ..., \overline{s}_{i-K}) \\
= &\sum_{s_{i-1},\overline{s}_{i-1},...,\overline{s}_{i-K}} P(\overline{s}_i = 1|s_i = 0, s_{i-1}, \overline{s}_{i-1}, ..., \overline{s}_{i-K}) * P(\overline{s}_{i-1}|s_{i-1}, ..., s_{i-L}, \overline{s}_{i-2}, ..., \overline{s}_{i-K}) \\
&P(s_{i-1}) * P(\overline{s}_{i-2}|s_{i-2}, ..., s_{i-L}, \overline{s}_{i-3}, ..., \overline{s}_{i-K})P(s_{i-2})... * P(\overline{s}_{i-K}|s_{i-K}, ..., s_{i-L}) \\
&P(s_{i-K})P(s_{i-K+1}, ..., s_{i-L})
\end{aligned} \tag{32}$$

where the term $P(\overline{s}_{i-1}|s_{i-1}, ..., s_{i-L}, \overline{s}_{i-2}, ..., \overline{s}_{i-K})$ can be defined as

$$\begin{aligned}
P(\overline{s}_{i-1}|s_{i-1}, ..., s_{i-L}, \overline{s}_{i-2}, ..., \overline{s}_{i-K}) = &\sum_{s_{i-L-1},\overline{s}_{i-K-1}} P(\overline{s}_{i-K-1}|s_{i-K-1})P(s_{i-L-1}) \\
&* P(\overline{s}_{i-1}|s_{i-1}, ..., s_{i-L-1}, \overline{s}_{i-2}, ..., \overline{s}_{i-K-1})
\end{aligned} \tag{33}$$

For obtaining a recursive form of the equation,

$$\begin{aligned}
P(\overline{s}_i = 1|s_i = 0) &= \frac{1}{2}\sum_{s_{i-1},\overline{s}_{i-1}} P(\overline{s}_{i-1}|s_{i-1})P(\overline{s}_i = 1|s_i = 0, s_{i-1}, \overline{s}_{i-1}) \\
&= \frac{1}{2^L}\sum_{s_{i-1},\overline{s}_{i-1}} P(\overline{s}_{i-1}|s_{i-1})... \sum_{s_{i-K},\overline{s}_{i-K}} P(\overline{s}_{i-K}|s_{i-K})P(\overline{s}_i = 1|s_i = 0, s_{i-1}, \overline{s}_{i-1}, ...\overline{s}_{i-K})
\end{aligned} \tag{34}$$

Thus,we get,

$$m = P(\overline{s}_i = 1|s_i = 0) = \frac{1}{2^L}\textstyle\sum_{s_{i-1}}\sum_{\overline{s}_{i-1},...,\overline{s}_{i-K}} Q(\lambda|_{s_{i-1},s_i=0}, \tau_{\overline{s}_{i-1},...,\overline{s}_{i-K}})\Pi_{j=1}^{K}\Psi(s_{i-1}, \overline{s}_{i-1}, m, n)$$

where, $\lambda_{s_{i-1},s_i=0} = \lambda_0 T + \sum_{j=1}^{L} s_{i-j}C_j$

Similarly,

$$n = P(\overline{s}_i = 0|s_i = 1) = \frac{1}{2^L}\textstyle\sum_{s_{i-1}}\sum_{\overline{s}_{i-1},...,\overline{s}_{i-K}} (1 - Q(\lambda|_{s_{i-1},s_i=1}, \tau_{\overline{s}_{i-1},...,\overline{s}_{i-K}}))\Pi_{j=1}^{K}\Psi(s_{i-1}, \overline{s}_{i-1}, m, n)$$

where $\lambda_{s_{i-1},s_i=0} = C_0 + \lambda_0 T + \sum_{j=1}^{L} s_{i-j}C_j$

1.4 Detailed derivation of performance metric-II

The second performance matrix is of BER v/s the received particles(r_i) which is mainly for the Zero-bit receiver. This metrics consists of plotting the performance of BER against the received particles when the signal i.e s_i is 0 and 1.

The probability function used here is:

$$P_{app}(r_i|s_i) = \frac{e^{\lambda|s_i}(\lambda|s_i)^{r_i}}{r_i!} \tag{35}$$

where

$$\lambda|s_i = C_0 s_i + \frac{\sum_{j=1}^{L} C_j}{2} + \lambda_0 T \tag{36}$$

Here, we have considered that the value of C_i are not known for $1 \leq i \leq n$ but the approximate value of $\frac{\sum_{i=1}^{L} C_i}{2}$ is known.

On imposing the equality $P_{app}(r_i = \tau|s_i = 0) = P_{app}(r_i = \tau|s_i = 1)$, we get the following value of the threshold(τ):

$$\frac{e^{\lambda|s_i=0}(\lambda|s_i = 0)^{r_i}}{r_i!} = \frac{e^{\lambda|s_i=1}(\lambda|s_i = 1)^{r_i}}{r_i!}$$

$$\frac{e^{\lambda|s_i=0}(\lambda|s_i = 0)^{\tau}}{\tau!} = \frac{e^{\lambda|s_i=1}(\lambda|s_i = 1)^{\tau}}{\tau!}$$

$$e^{\lambda|s_i=0}(\lambda|s_i = 0)^{\tau} = e^{\lambda|s_i=1}(\lambda|s_i = 1)^{\tau}$$

where

$$\begin{aligned}(\lambda|s_i = 0) &= 0 * C_0 + \frac{\sum_{j=1}^{L} C_j}{2} + \lambda_0 T \\ &= \frac{\sum_{j=1}^{L} C_j}{2} + \lambda_0 T\end{aligned}$$

$$\begin{aligned}(\lambda|s_i = 1) &= 1 * C_0 + \frac{\sum_{j=1}^{L} C_j}{2} + \lambda_0 T \\ &= C_0 + \frac{\sum_{j=1}^{L} C_j}{2} + \lambda_0 T\end{aligned}$$

So, putting the values we get,

$$e^{\frac{\sum_{j=1}^{L} C_j}{2} + \lambda_0 T}\left(\frac{\sum_{j=1}^{L} C_j}{2} + \lambda_0 T\right)^{\tau} = e^{C_0 + \frac{\sum_{j=1}^{L} C_j}{2} + \lambda_0 T}\left(C_0 + \frac{\sum_{j=1}^{L} C_j}{2} + \lambda_0 T\right)^{\tau}$$

$$e^{C_0} = \frac{(\frac{\sum_{j=1}^{L} C_j}{2} + \lambda_0 T)^\tau}{(C_0 + \frac{\sum_{j=1}^{L} C_j}{2} + \lambda_0 T)^\tau}$$

$$e^{C_0} = \frac{1}{(\frac{C_0}{\frac{\sum_{j=1}^{L} C_j}{2} + \lambda_0 T} + 1)^\tau}$$

On taking logarithm on both the sides we get,

$$\tau_{subopt} = \frac{C_0}{\ln(1 + \frac{C_0}{\frac{\sum_{j=1}^{L} C_j}{2} + \lambda_0 T})}$$

For the derived threshold value, we obtain the value of the approximated distribution, i.e. the P_{app} for $s_i = 0, 1$

$$P_{app}(r_i|s_i = 0) = \frac{e^{\lambda|s_i=0}(\lambda|s_i = 0)^{r_i}}{r_i!} \tag{37}$$

$$P_{app}(r_i|s_i = 1) = \frac{e^{\lambda|s_i=1}(\lambda|s_i = 1)^{r_i}}{r_i!} \tag{38}$$

The optimal value of the threshold is obtained by equating the BER equation:

$$(\tau^*, P_e^*) = argmin_\tau P_e(\tau) \tag{39}$$

2 Numerical Results(Analytical Model)

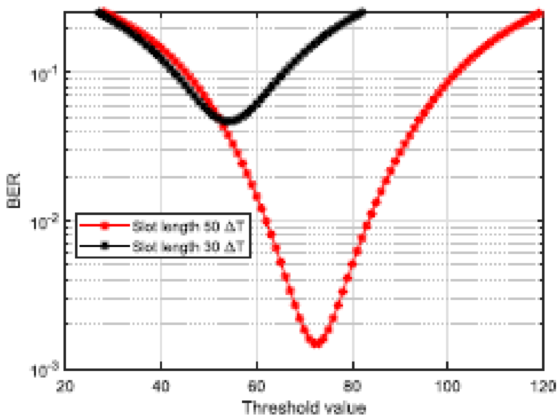
2.1 Simulation Framework

We have performed all the simulations in the MATLAB online verion.(MATLAB Online R2020b) The parameters which we have used are:

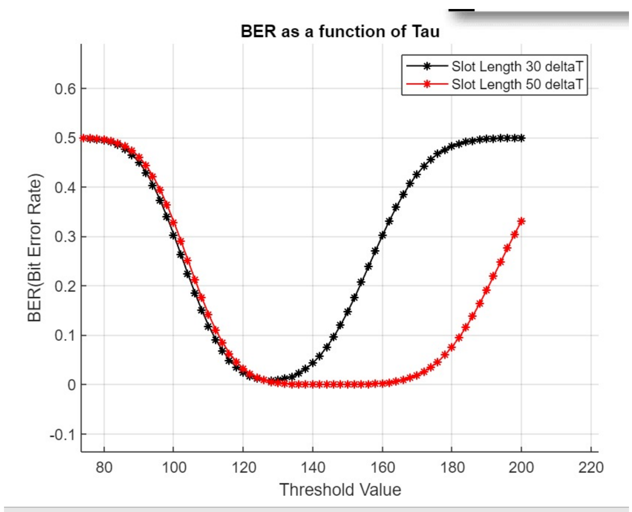
Symbol	Description	value
λ_0	background noise power per unit time	$100s^{-1}$
r	Receiver radius	45 nm
d	Distance	500 nm
D	Diffusion coefficient	$4.265 * 10^{-10} m^2/s$
ΔT	Discrete time length	9 us
T	Slot length	$30\Delta T$
L	Channel length	5

2.2 Reproduced Figures

- Reproduced Figure-1



(a) Figure 1B

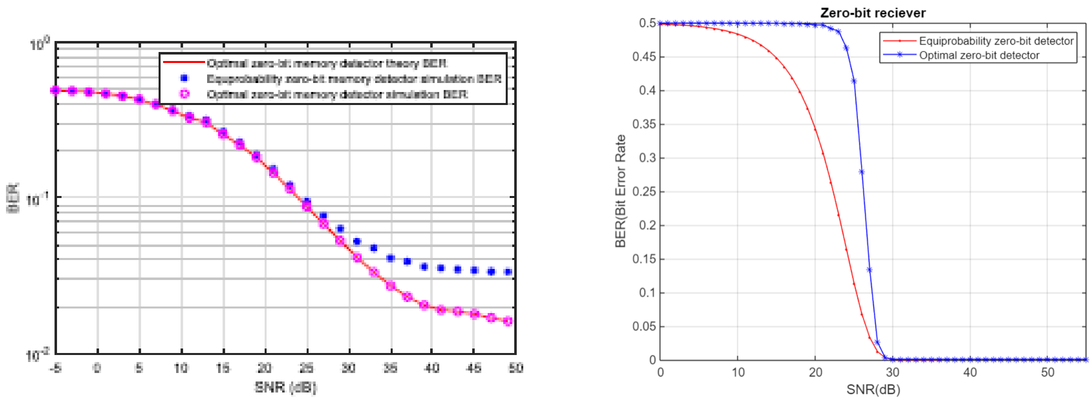


(b) Figure 1R

Figure 2: BER as a function of τ (SNR=30dB)

For a fixed value of SNR,and for a given slot length ($30\Delta T$),we get a optimal value of threshold that can minimise the BER which depends on the slot length.Also the threshold value increases as we increase the slot length which more minimises the BER.

- Reproduced Figure-2



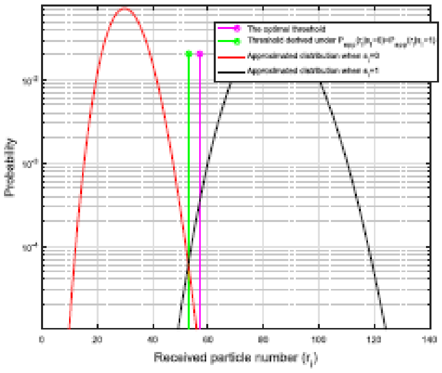
(a) Figure 2B

(b) Figure 2R

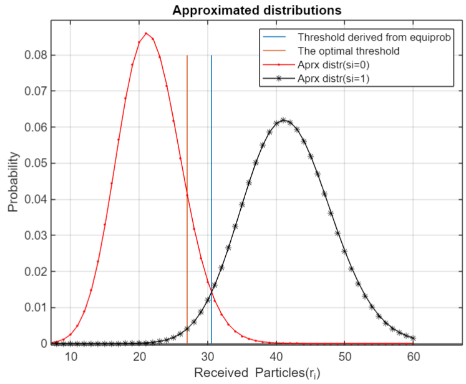
Figure 3: BER of optimal vs conventional zero-bit receiver(T=30ΔT)

For a fixed slot length(time slot duration i.e. here $30\Delta T$),we have plotted the graph of BER vs SNR for zero bit receiver. The optimal threshold value graph provides a better BER performance as compared to that pf the sub-optimal threshold value graph.

- Reproduced Figure-3



(a) Figure 3B

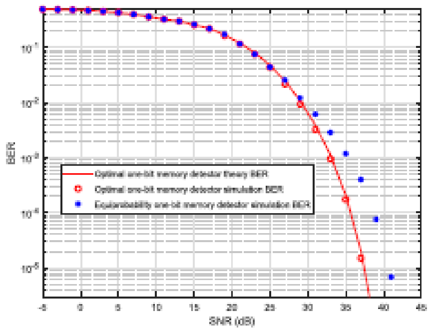


(b) Figure 3R

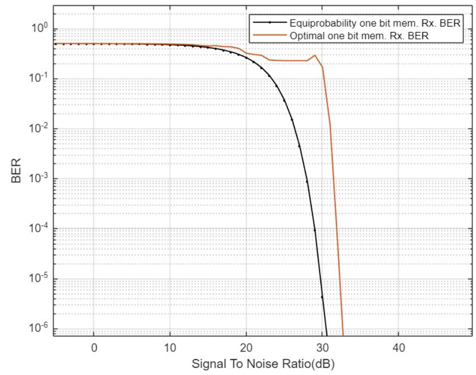
Figure 4: Approximated distributions of the received particles(SNR=25dB)

The value of optimal threshold and the approximated probability threshold.This figure demonstrates the sub-optimality of the zero-bit receiver design. These approximated distributions cross each other at the threshold obtained by $P_{app}(r_i|s_i = 0) = P_{app}(r_i|s_i = 1)$ rather than crossing at the optimal threshold which shows that the sub-optimal value cannot have performance as good as the optimal value.

- Reproduced Figure-4



(a) Figure 4B

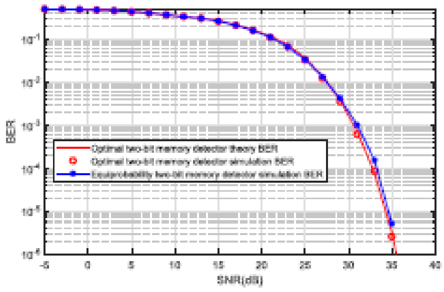


(b) Figure 4R

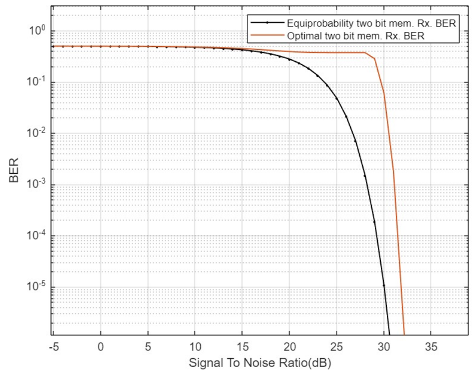
Figure 5: BER of optimal vs sub-optimal one-bit receiver(T=30ΔT)

For a fixed slot length(time slot duration i.e. here $30\Delta T$),we have plotted the graph of BER vs SNR for one bit receiver. The optimal threshold value graph provides a better BER performance as compared to that pf the sub-optimal threshold value graph.The gap between the optimal and the sub-optimal receiver reduces as ISI is more accurately calculated.

- Reproduced Figure-5



(a) Figure 5B



(b) Figure 5R

Figure 6: BER of optimal vs sub-optimal k-bit receiver(T=30ΔT)

For a fixed slot length(time slot duration i.e. here $30\Delta T$),we have plotted the graph of BER vs SNR for k bit(2-bit) receiver. The optimal threshold value graph provides a better BER performance as compared to that pf the sub-optimal threshold value graph.The gap between the optimal and the sub-optimal receiver reduces as ISI is much more accurately calculated and almost both the graph merges into one.

3 Performance Analysis of Base Article(Data Model)

3.1 List of symbols and their description:

Symbol	Description	value
λ_0	background noise power per unit time	$100s^{-1}$
r	Receiver radius	45 nm
d	Distance	500 nm
D	Diffusion coefficient	$4.265 * 10^{-10} m^2/s$
ΔT	Discrete time length	9 us
T	Slot length	$30\Delta T$
L	Channel length	5

- **3.2 Network Model**

This is basically Data driven format of the above system model. As the Deep Learning tools help us in detection without any prior knowledge of the channel model. Here there is no assumption of perfectly known system model. Here we are taking ANN(Artificial Neural Network) with fully connected layers and deep learning to optimize design of molecular receiver. ANN consist Input layer, some hidden layer and Output layer, which is shown in this figure.

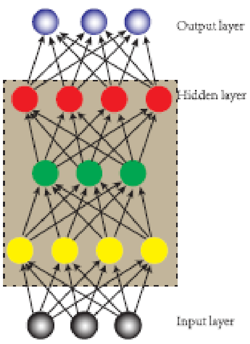


Figure 7: ANN with fully connected layer

3.3 Detailed derivation of performance metric

Same as system model, the ANN can be described for three type of receivers :

– **Zero-bit Memory Receiver**:

It is a system whose input is received information particles r_i at i-th time slot, and the output are the probabilities that the transmitted bit is 0 or 1, $Pi(si = 0|ri)$ and $Pi(si = 1|ri)$, respectively. [6]

And also, $Pi(si = 0|ri) + Pi(si = 1|ri) = 1$

$\therefore$ We have to find any one of them, so

$$\bar{s_i} = \begin{cases} 0 & , \mathrm{P}_i \leq 0.5 \\ 1 & , \mathrm{P}_i \gneq 0.5 \end{cases} \tag{40}$$

– **One-bit Memory Receiver**:

In this case, ANN not just depend on received particles at ith time slot, but also on previous one estimates symbol at (i-1)th slot as $\bar{s}_{i-1}$.

$\therefore$

$$\bar{s_i} = \begin{cases} 0 & , \mathrm{P}_i(S_i = 1|\mathrm{r}_i, \bar{s}_{i-1}) \leq 0.5 \\ 1 & , \mathrm{P}_i(S_i = 1|\mathrm{r}_i, \bar{s}_{i-1}) \gneq 0.5 \end{cases} \tag{41}$$

– **K-bit Memory Receiver**:

By extending the logic on one bit receiver to k bit receiver the decision rule is describe as,

$$\bar{s_i} = \begin{cases} 0 & , \mathrm{P}_i(S_i = 1|\mathrm{r}_i, \bar{s}_{i-1}, \bar{s}_{i-2}, ..., \bar{s}_{i-K}) \leq 0.5 \\ 1 & , \mathrm{P}_i(S_i = 1|\mathrm{r}_i, \bar{s}_{i-1}, \bar{s}_{i-2}, ..., \bar{s}_{i-K}) \gneq 0.5 \end{cases} \tag{42}$$

4 Numerical Results

4.1 Simulation Framework

The parameters used in the simulation work are as follows.The simulation of the data modelling is done in the Google COLAB files.

Parameters	**value**
Hidden layers	10
neurons per layer	5
learning rate	0.01
training epoch	200
training bits	300
batch	5

4.2 Data Generation

- Generated data contains 300 samples with two column 1^{st} is transmitted bit and the 2^{nd} one is received bit.
- data generation is done using the equation of the system model part, and we have used the value of the parameters from the table.
- Here is the pseudo-code for generating the data:

Algorithm 1 Pseudo-code for generating data(Data of 300 samples of transmitted and received bit)

initialization of the parameter given in the table

$P_0 = \frac{r}{d} erfc\left(\frac{d-r}{\sqrt{4Dt}}\right)$

$N_t x = 2\lambda_0 T \frac{10^{\frac{snr}{10}}}{P_0}$

$C_0 = N_t x * P_0$

$check = random(1, channelLength)$

i=0

while $channelLength = i$ **do**

  if $check[0][i] \gnsim 0$ **then**

    $P_j[0][i] = 1$

  end if

  i = i+1

end while

while NTx = i **do**

  $P_{i-1} = \frac{r}{d}\left(erfc\left(\frac{d-r}{\sqrt{4Dt}}\right) - erfc\left(\frac{d-r}{\sqrt{4Dt}}\right)\right)$

  $C_j[i] = N_{Tx}[i] * P_{i-1}[i]$

  $I_i = \lambda_0 T + \sum_{j=1}^{\infty} s_{i-j} C_j$

  recievedSignal = poisson($I_i + s_i C_0$)

  print(receivedSignal)

end while

- Here is the link of the Data generation code link and link of the generated data.
  1. Data generation
  2. ANN

5 Contribution of team members

5.1 Technical contribution of all team members

Tasks	**Aanshi Patwari**	**Dipika Pawar**	**Miracle Rindani**	**Mithilesh Thakkar**
Analytical Model Derivation	✓		✓	
Analytical Model Simulation	✓		✓	
Data Model Derivation		✓		✓
Data Model Simulation		✓		✓

5.2 Non-Technical contribution of all team members

Tasks	**Aanshi Patwari**	**Dipika Pawar**	**Miracle Rindani**	**Mithilesh Thakkar**
Analytical Model Report	✓		✓	
Data Model Report		✓		✓
MIRO mind mapping	✓	✓	✓	✓

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