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

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

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- Project Title:

  Base Article: [1] X. Qian, M. Di Renzo, and A. Eckford, “Molecular communications: Model-based and data-drivenreceiver design and optimization,”IEEE Access, vol. 7, pp. 53 555–53 565, 2019.

1 Introduction

1.1 Background

- Molecular communication was introduced when there arose a need for communication in nanodevices, where electromagnetic communication is not possible. In molecular communication, information particles are used to transmit data.Information is encoded into particles, which are then released into the channel and absorbed at the receiver. Some of the major challenges with molecular communication are controlled propagation of the particles, design of systems devised for transmission and reception and the way encoding or decoding of information particles is done.

- According to the base article, Concentration Shift Keying (CSK) is the scheme which is used for modulation of the transmitting particles.The motivation for choosing CSK is that it takes into account the concentration of particles which will help to detect the symbol transmitted using threshold based receivers.CSK encodes the information particles into 0 or 1. When 1 is transmitted, a total of Ntx particles are transmitted and when it is 0, no particles are transferred from transmitter to receiver.Design of the system comprises of a point transmitter and a spherical receiver. The above technique is however utilised for model based detection scheme. A newer approach which is Data-driven approach proves to be more efficient since it does not require foreknowledge of channel state information on the receiver side. Deep Learning methods are used to overcome the above mentioned limitation. Artificial Neural Networks is used as a learning framework in our article. ANNs provide same performance as the conventional methods that rely on the perfect knowledge of the system and so they are more feasible to implement in molecular communication system where prior knowledge is not always known.

- The MCvD system model mentioned in [1] is widely accepted and prevalent since it imitates biological process and does not require additional infrastructure to be implemented. [2] uses a diffusion based molecular communication system and reviews the effects different properties of this system; including free diffusion and advection. [2] also reviews the models existing in the literature for the transmitter and receiver, and also the different assumptions such as point transmitter, fully/partially absorbing receiver, different transmission channels etc. while deriving mathematical expressions for the same. [3] considers the MCvD model to propose an analytical expression to determine optimal threshold using various distribution parameters for demodulating the received particles. [4] propose the use of a Machine Learning framework such as ANN to optimize the receiver performance, and [5] proposes RNN and SBRNN frameworks for detection. [6] describes a vesicle based design of a MC system to improve the propagation system and reduce the ISI. While, [7] comprehensively review the ATMC model and describe the possible approaches to improve the overall propagation, [8] propose an energy-based model for ATMC using vesicles. [9] provides a comprehensive summary of the vesicle-based approach in ATMC.

  Another approach to improve receiver performance is using enzyme degradation as described in [10], in which they also derive mathematical expressions for transmitted and received particles including diffusion and reaction-diffusion equations.

  [11] and [12]have surveyed and reviewed the future possibilities for research pertaining to the molecular communication paradigm and have also mentioned the recent advancements in the field. A major application is a targeted drug delivery system as described in [13].

  [14] provides a literature review of physical designs of transmitter and receiver, as well as various modulation, coding and detection techniques. [15] is a recent model that uses a two-way MCvD system, investigating a half-duplex as well as a full-duplex system, which increases the complexity of the MCsystem.

1.2 Motivation

Molecular communication is a relatively new domain and thus, not a lot of literature is available for the same. On the other hand, the available literature is quite explicit. The transmission has been approached in many ways including the relative time of release, the type of particles, their concentration released and the mode of transmission too can have different models. The system model that has been explored in the base article has been assumed to have perfect CSI and there is no provision to curb ISI(intersymbol interference). This leads to an inaccurate estimation of symbols at the receiver. Although ISI cannot disappear completely, we have introduced an enhancement to the existing system model that might abate it to some extent. Another approach we have made is towards the improvisation of the neural network in use for the estimation of symbols. Our base article has used ANN(artificial neural networks), but we have tried to use LSTM(long short-term memory) RNN in the same context as it takes classification decisions based on the history of inputs and the corresponding decisions.

1.3 Contributions

- This paper proposes different threshold based schemes both including model based detection schemes and Data driven based detection schemes. Both model takes ISI and background noise into account and aims at reducing these parameters in order to increase BER performance with appropriate threshold calculations. Model based approaches include optimal ZERO BIT and ONE BIT memory receiver by assuming prior knowledge of system model. However, Data driven approaches gives the optimum threshold for the detection schemes that outputs same performance as the model based conventional approaches without assuming any prior knowledge of the system model at the receiver side.

- **Vesicle based propagation**:

  To reduce or eliminate the effect of inter-symbol interference or the possibility of chemical reactions of the particles in the propagation channel, we consider a micro channel molecular communication system consisting of nano-scale information carriers (i.e., molecules or vesicles). These vesicles cover the diffused particles and protect them from interacting chemically with other symbols in the medium. This method is existing in the literature in the model with Brownian motion as well as the models with active transfer-based molecular communication(ATMC). While ATMC using micro tubules and motor molecules, typically a kinesis system, assures reliable transfer of the particles to the receiver; it is not ideal for a drug delivery system in the human body as it consumes precious ATP from the environment to drive its motors. Thus, we assume that the information particles diffuse randomly and independently of each other through the medium (Brownian motion).

- **Channel impulse response for passive receiver**: Channel impulse response of the end to end channel is denoted by h(t) as the probability of observation of one output molecule at time interval t at the receiver side when the transmitter is stimulated in an impulsive manner at time $t_o = 0$ In our channel model we have considered a passive spherical receiver. For passive receivers, the set of all points d inside the volume of the receiver, V_{rx},constitutes the area under consideration and N_{tx} denote the number of molecules that the transmitter releases.

- **Enzymatic degradation:** Enzymes are used in the propagation environment due to their selectivity and because a single enzyme can be recycled to react many times. There are 3 diffusive molecular species in the system that we are interested in: A molecules that carry the information, E molecules comprising of enzymes and EA molecules of intermediate formed by A and E. Enzymatic reaction can be given as follows after applying Michaelis-Menten kinetics,

  E+A$\rightarrow EA$

  $EA \rightarrow E + A$

  $EA \rightarrow E$+A$_p$

  Where EA is the intermediate formed by the binding of an A molecule to an enzyme molecule, Ap is the degraded A molecule and k_1, k_{-1}, and k_2 are the reaction rates for the reactions as shown with units $molecule^{-1}m^3s^{-1}, s^{-1}$, and s^{-1} , respectively.

- Another data driven framework called Artificial Neural Network that is capable of estimating optimal threshold that minimizes BER taking ISI into account without any knowledge of the system model. This implementation is based on feed-forward ANNs consisting of fully connected layers. Each layer in ANN takes input from the previously detected symbol and the current number of particles at the receiver. This ML based approaches are less complex and easier to implement.
- A novel LSTM based framework for detection of the transmitted symbol at the receiver in which the previous estimated symbols are fed along with the present number of particles in order to increase the performance of the model assuming no channel knowledge provided at the receiver. It is capable of storing memory and have the ability to exercise long term dependencies that overcomes the problem of other neural networks and outperforms with efficient accuracy and low BER. At the end, results showing Accuracy based graph indicate remarkable performance in LSTM simulation in comparision with ANN for generating more optimal threshold for classification.

2 Performance Analysis of Base Article

2.1 List of symbols and their description

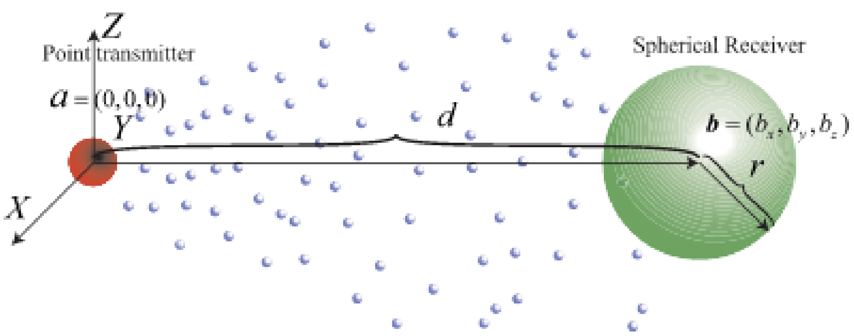
Parameter	Description
λ_o	Background noise power per unit time
r	Receiver radius
d	Distance between transmitter and centre of the receiver
ΔT	Discrete time length
T	Slot length
L	Channel length

2.2 System Model

Channel: Diffusion through brownian motion

Transmitted signal: Information particles (0 or 1) BPSK

Nature of noise: Background noise and ISI



2.3 Derivations of performance metric

- Here, s_i is the symbol to be transmitted. The number of particles transmitted depends on whether 0 is to be transmitted or 1.

$$\text{If } s_i = 1,\ N_{TX} \text{ particles are transmitted}$$
$$\text{If } s_i = 0, \text{ no particles are transmitted}$$

- The particles reach the receiver at different instances of time. This causes ISI (intersymbol interference). Thus, the hitting rate of each particle is

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

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 is given by

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

So, the probability that one particle hits R_x at the $(i-1)$th time slot is

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

The average number of particles received at the jth time slot, if N_{TX} particles are released is given by

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

The received particles r_i is given by

$$r_i \sim Poisson(I_i + s_iC_0) \tag{5}$$

where $I_i = \lambda_0 T + \sum_{j-1}^{L} C_j s_{i-j}$
$\therefore$ The probability of receiving r_i particles is

$$P(r_i|I_i + s_iC_0) = \frac{e^{-(I_i+s_iC_0)}(I_i + s_iC_0)^{r_i}}{r_i!} \tag{6}$$

The SNR is given by

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

Putting the value of C_0 in equation(7),

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

This gives the number of particles released from T_x.

- Optimal Zero Bit Memory Receiver: $\bar{s_i}$ denotes estimate of symbol s_i at time slot i. Demodulation rule:

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

τ is obtained by $P(r_i = \tau | s_i = 0) = P(r_i = \tau | s_i = 0)$

$$P(r_i|s_i) = \frac{e^{\frac{-\lambda}{si}}(\frac{\lambda}{si})^{ri}}{r_i!} \tag{10}$$

$$\frac{\lambda}{si} = \lambda_o T + C_o si + \frac{\sum_{j=1}^{L} C_j}{2} \tag{11}$$

$$\frac{e^{-\lambda|si=0}(\lambda|si=0)^{ri}}{r_i!} = \frac{e^{-\lambda|si=1}(\lambda|si=1)^{ri}}{r_i!} \tag{12}$$

- Thus, suboptimal threshold is given by

$$\tau = \frac{C_0}{ln\left(1 + \left(\frac{C_0}{\sum_{j=1}^{L}\frac{C_j}{2} + \lambda_0 T}\right)\right)} \tag{13}$$

- Optimal one bit receiver

$$\bar{s_i} = \begin{cases} 0 & \text{if } r_i \leq \tau | s_{i-1} \\ 1 & \text{if } r_i > \tau | s_{i-1} \end{cases} \tag{14}$$

$$m = \frac{1}{2^L}\sum_{s_{i-1}}\sum_{\bar{s}_{i-1}} Q(\lambda|_{(s_{i-1}, s_i=0)}, \lceil \tau|_{\bar{S_i}} \rceil)\psi(s_{i-1}, \bar{s}_{i-1}, m, n) \tag{15}$$

$$n = \frac{1}{2^L}\sum_{s_{i-1}}\sum_{\bar{s}_{i-1}} 1 - Q(\lambda|_{(s_{i-1}, s_i=1)}, \lceil \tau|_{\bar{S_i}} \rceil)\psi(s_{i-1}, \bar{s}_{i-1}, m, n) \tag{16}$$

where $\psi(s_{i-1}, \bar{s}_{i-1}, m, n)$,

$$\psi(s_{i-1}, \bar{s}_{i-1}, m, n) = \begin{cases} m, s_{i-1} = 0, \bar{s_{i-1}} = 1 \\ 1 - m, s_{i-1} = 0, \bar{s_{i-1}} = 0 \\ n, s_{i-1} = 1, \bar{s_{i-1}} = 0 \\ 1 - n, s_{i-1} = 1, \bar{s_{i-1}} = 1 \end{cases} \tag{17}$$

3 Performance Analysis of New contributions

3.1 Changes in system model

3.1.1 Vesicle based propagation

In the existing paper, the authors have assumed the diffusion coefficient to be constant (by keeping temperature and viscosity constant).Diffusion D in a propagation environment is given by: D=$\frac{kBT}{6\pi\eta RH}$

It is still possible that not all transmitted particles arrive at the receiver after a certain fixed time has elapsed. If x particles left the transmitter, and only y were received and P_a represent the probability that a given vesicle will arrive at the receiver. Thus $f(y|x)$ has a possible binomial distribution, given by

$$f(y|x) = \binom{x}{y} P_a^y (1 - P_a)^{x-y}$$

With this PMF and the PMF f(x) , we can find the channel capacity; the maximum rate at which the information can be sent through the channel. We can see that because of the vesicles, the channel capacity improves as more number of particles are received on the receiver and thus effectively reducing the ISI.

Thus, while modeling the mass-transfer based system, we get the net error as:

$$I_i = \lambda_o t + \sum_{j=1}^{\infty} s_(i - j)C_j$$

. In which, $\lambda_o t$ is the background noise (caused by external particles interacting with the information particles) and the other term is the ISI due to previously diffused particles.The vesicles effectively reduce the external interaction of the non-information particles as well as the effect of previously diffused particles that are still there in the channel.This is shown by experimental observations.

3.1.2 Channel impulse response for passive receiver

We consider $p(d,t) = c(d,t)|N_{tx} = 1$ which can be interpreted as the PDF of a molecule released by the transmitter at $t_o = 0$ with respect to d at time t. Also it can be interpreted as $p*(d,t)dxdydz$ is the probability that the molecule is observed in volume $dxdydz$ at time t. If we focus on linear systems then solving $c*(d,t)$ with $N_{tx} \neq 1$and solving p*(d,t) for Ntx=1 are related as

$$p*(d,t) = c*(d,t)|N_{tx}$$

In our case with point transmitter and unbounded environment, the channel impulse response of a passive receiver can be obtained by p(d,t) with initial and boundary conditions.
Initial condition:

$$p(d,to) = (d - dtx)$$

Boundary condition:

$$p(||d||,t) = 0$$

Given the solution for $p*(d,t)$, h(t) can be written as, $h(t) = \int_d p*(d,t)dd$, The solution for h(t) can be easily obtained when the receiver is sufficiently far away from the transmitter, i.e, d_o is very large relative to the largest dimension of the receiver.We consider a common approach in this case which is referred to as the uniform concentration assumption, is to approximate p*(d,t) everywhere inside the volume of the receiver by its value at the center of the receiver, i.e, $p*(d,t) = p*(d_{rx},t)$ for all d in V_{rx}

Channel impulse after all above considerations is given by:

$$h(t) = (\frac{V_{rx}}{4\pi Dt}^{3/2})exp^{-\frac{d_o^2}{4Dt}}$$

3.1.3 Enzyme based degradation

The interference term in our channel model is represented by:

$$I_i = \lambda_o t + \sum_{j=1}^{\infty} s_(i-j)C_j$$

In which, $\lambda_o t$ is the background noise (caused by external particles interacting with the information particles) and the other term is the ISI due to previously diffused particles.Taking enzymes into consideration will reduce the effect of ISI as the chemical reactions between outside particles and transmitted particles will lessen.

3.2 LSTM framework

This paper includes deep learning tools that helps to increase the performance of detection without any prior knowledge of the channel model. We proposed two Data-Driven schemes that are used in MC systems – Artificial Neural Network (ANN) and Long Short Term Memory (LSTM). Since, traditional ANNs lacks in storing information because of unavailability of memory elements. Moreover, in our case, the data is time-series data as we are sending symbols at different time slots and this can be best modeled by a type of recurrent neural network known as Long Short Term Memory (LSTM) network. The have an advantage over simple RNNs as they can model long term dependencies.

3.2.1 SYSTEM MODEL & LSTM PRELIMINARIES

The detection model at the receiver side can be formulated as a Binary Classification problem. The input to the training model is the number of particles received at the spherical receiver at different time slots on a particular SNR and output of the model is the estimated symbol transmitted from the transmitter. In the training model, LSTM uses previous predicted symbol is fed with the current received particles in order to predict the estimated symbol of the next time slot. The vectors representing the input and output are described as below:

$y = [y^{<1>} \quad y^{<2.} \quad y^{<3>}.. \quad y^{<N>}]$ - input vector (number of particles)

$a = [a^{<1>} \quad a^{<2.} \quad a^{<3>}.. \quad a^{<N>}]$ - output vector (symbol detcted)

where N is the number of time slots at each particular SNR.

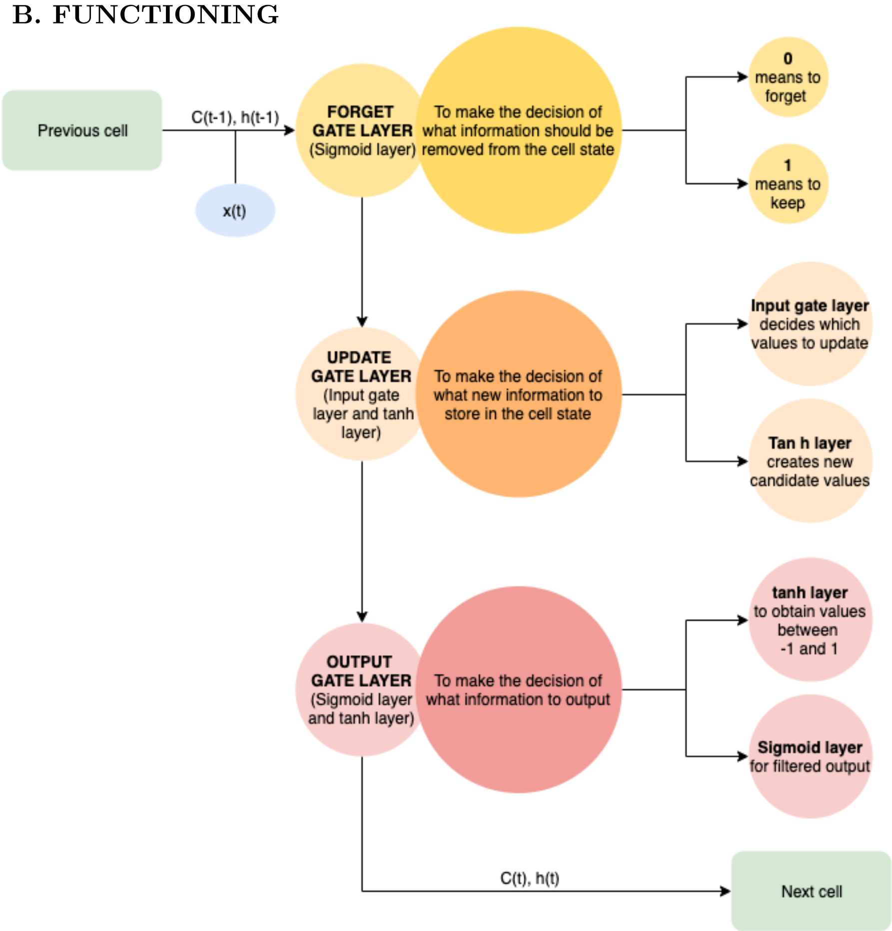
Fig1. shows the internal structure of an LSTM cell in which the input where $y^{<t>}$ is the input, $a^{<t>}$ is the output of the LSTM cell, $a^{<t-1>}$ is the previous LSTM output, an $c^{<t>}$ and $c^{<t-1>}$ are the current and previous cell states, respectively. The details of the LSTM cell is explained below:

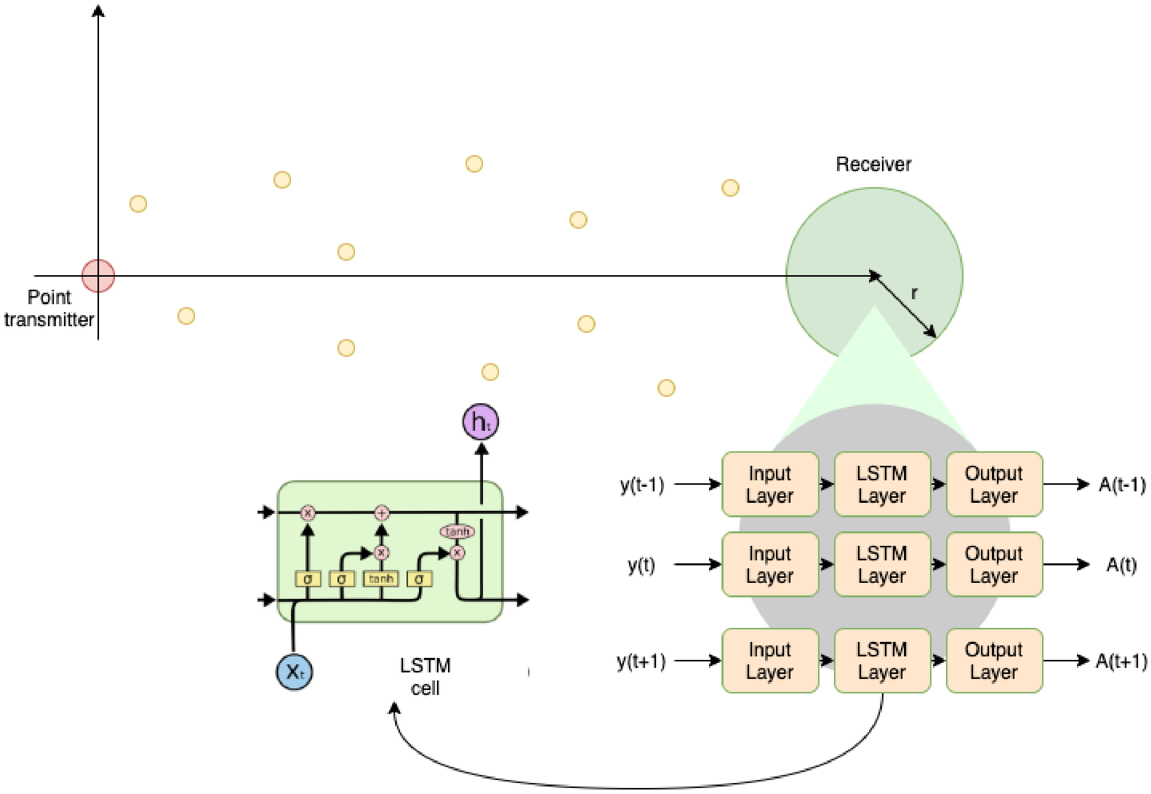
A. KEY SUB PARTS OF THE LSTM CELL

An LSTM cell has the following key elements:

1. Update gate: Makes the decision to update current cell state.
2. Forget gate: Makes the decision of when to discard the current cell.
3. Output gate: Controls the filtering of the parts to output.

B. FUNCTIONING





3.2.2. LSTM and ANN Training

Since ANN goes through a drawback of not having the capacity of storing the memory elements, hence there is a need to modify the current ANN neural network that is a type of RNN knows as LSTM. Fig 2 incorporates the idea of LSTM layer inside the model used at the receiver side. It shows the different LSTM layers used between the input and output layers and further, it shows the structure of the LSTM cell that is present inside each of the LSTM layers in the form of neurons.

A. DATA-SET CONSTRUCTION

The proposed LSTM model is trained based on the data captured at different time slots. For each SNR, total number of particles that must be transmitted by the transmitter, i.e., Ntx is computed by the formula described above. Further, we compute the probability that one particle hits the receiver and average number of particles hitting the receiver at each time slot by using the below equations :

Probability that one particle hits the receiver:

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

Average number of particles at the jth time slot :

$$C_j = Ntx * P_j$$

Furthermore, Calculating $I_i + s_i C_0$ where $I_i = \lambda_0 * T + \sum s_{i-j} C_j$, we find the number of particles r_i using Poisson random function.

Hence, we make two files one containing the number of particles received at the receiver which is taken by the variable r_i and the transmitted symbols from the receiver at that particular time slot which is given by the variable s_i. For each SNR, there are 100 time slots and hence, the both the files including number of particles and symbols detected are in the number of 100. Moreover, 80% Dataset is used for training and 20% remaining is used for testing the dataset.

Procedure Create Dataset

$(snr, lambda, slot_length, distance, radius, channel_length, time_slot, diffusion_coefficient, transmitted_particles, receive$

1. Compute number of particles released
2. for i = 1 to length of slot-length do
3. compute probability of hitting the receiver;
4. for i = 1 to length of slot-length do
5. compute average number of particles number of particles released * probability of hitting the receiver;
6. c0 = 54
7. sum = summation of transmitted particles * average number of particles over all time slots
8. avg = lambda * slot$_{l}ength + sum + transmittedparticles * c0$
9. received$_{p}articles = randomnumbersfromPoissonDistributionwithrateparameteravg$
10. A = [received$_{p}articles; transmitted_{p}articles$]
11. return A

B. LSTM TRAINING & MODEL SELECTION

The LSTM code uses Keras Library that is used to train the model and test it in accordance with the dataset. The dataset has two files - one containing the number of particles reached at many time slots which is mainly our input, and the symbol detected for each time slot which is considered as output. Our model is a binary classification model that classify the number of particles into 0 or 1 classes that are referred to as symbols detected. The model uses 80% of the dataset for training itself and 20% for testing and outputting the accuracy of the model in detecting the correct symbol. This model uses Embedding layer that takes in input of length 1 and we specify the mutually exhaustive possibilities of the values of number of particles at each time slot. Further, we add the LSTM layer with 100 neurons that is helpful in making the detection more efficient as compared to other techniques like Artificial Neural Nets and Recurrent Neural Nets. As we increase the number of hidden units, training accuracy risesup. At the end, the output layer also has one output and uses the sigmoid function. It uses binary cross entropy function as the loss function which tries to minimise the error rate and tries to increase the accuracy. We have used 'adam' as our optimiser in order to update the weights in training data instead of using classical gradient descent.

Table 1. **Hyperparameters for the proposed scheme-II**

Hyperparameter	**Value**
Batch Size	30
Number of epochs	40
No of hidden layers	3
No of neurons in each layer	100
Loss Function	Cross Entropy

C. ANN TRAINING & MODEL SELECTION

The ANN code uses tensorflow and pyrenn libraries in order to define and train the model. It divides into testing and training. Training comprises of 80% of data and testing comprises of remaining 20% of it. Each dataset corresponds to one SNR and has 100 data items in both input and output that depicts the number of time slots. Since our system uses one input and 1 output, the neural network model is specified with these parameters. We took the network that has 6 hidden layers comprising of 10 neurons each. Specifically, we use the Bayesian regularization back-propagation technique, which updates the biases and weights by using the Levenberg- Marquardt (LM) optimization algorithm. The data inputted in the model for training is in the form of batches whose length is decided by the batch size parameter specified in order to reach the maximum accuracy. The batch size specified is 10. Furthermore, We calculate the output of the test data using this ANN model and compare it with actual output to compute the error rate.

D. EVALUATION OF PERFORMANCE METRIC

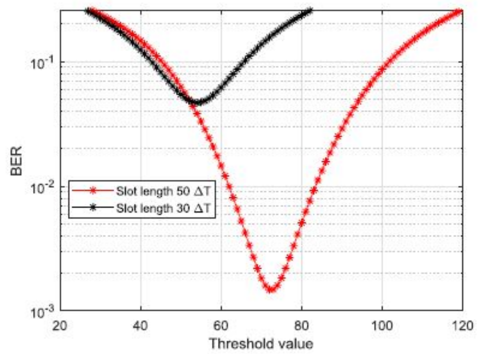
The final results generated by the ANN simulation and LSTM simulation include two performance metrics naming Accuracy and BER. The model takes in input the number of particles received at the receiver and outputs the symbol detected. First, this process takes place to train the model for a particular SNR, and test the same model for the test dataset values on that particular SNR. The model outputs the accuracy obtained after testing the test dataset values and also returns the estimated symbol calculated which is further compared with the original test output data to calculate the number of bit errors. Hence, ANN and LSTM model outputs Accuracy and corresponding BER. It is observed by seeing in the Table 2., that Long Short Term Memory (LSTM) framework outperforms Artificial Neural Network (ANN) due to its ability to store memory elements and basically having long-term dependencies. Moreover, the figure in New results depict the Accuracy graph which infers the same result.

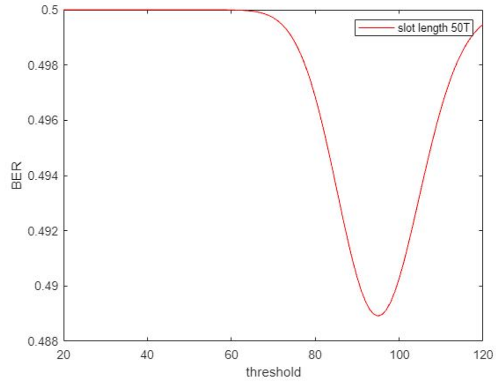
SNR	**Accuracy(ANN)**	**Accuracy(LSTM)**
10	40%	75%
15	55%	95%
20	75%	90%
25	55%	80%
30	60%	85%
35	60%	70%
40	55%	75%
50	60%	70%

4 Numerical Results

4.1 Reproduced Figures

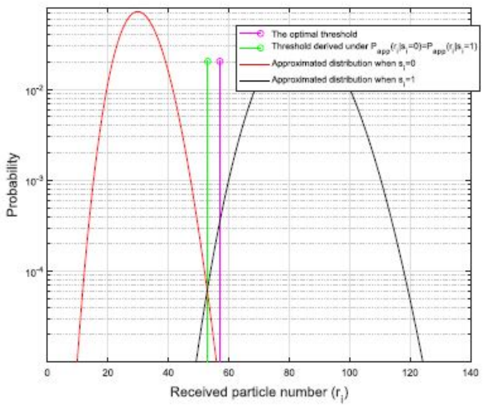
- **BER in as a function of τ**

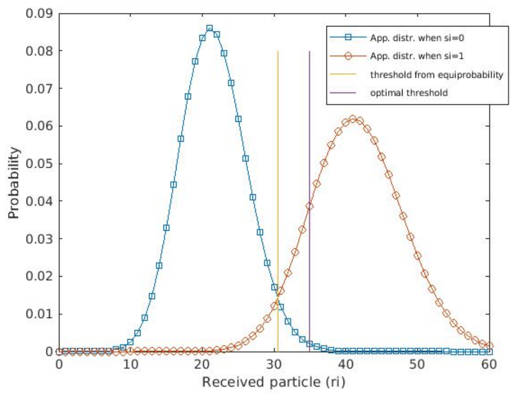




The graph shows the relation between the threshold value and the BER. The optimal threshold can be obtained by looking at the minimum value of the BER corresponding to a particular slot length. On increasing slot length the BER performance decreases.

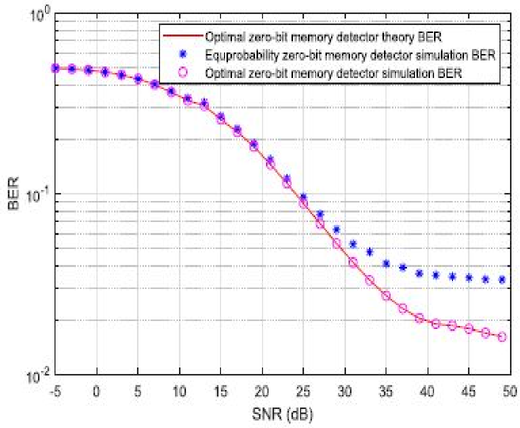
- **Approximated distributions of the received bits**

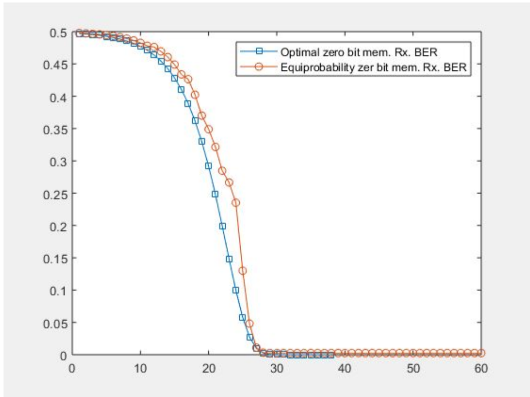




The graph shows trends of sub-optimal and optimal thresholds. And the 2 curves show the approximate distribution when the symbol $s_i = 0$ and $s_i = 1$.The optimal threshold is more idealistic in comparison to sub-optimal threshold.

- **BER of optimal vs. conventional zero-bit memory receiver**



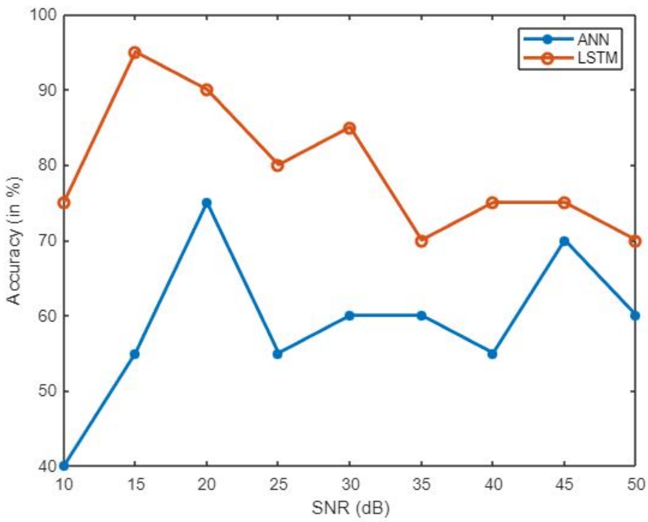


This graph shows both simulated and theory curves of optimal zero bit detector and one additional curve of equi-probability zero bit memory detector simulation BER. It shows that BER performance of optimal threshold is better than BER performance of sub optimal threshold.

4.2 New Results

- **Accuracy v/s SNR graph**

  This graph plots the Accuracy generated by both the Data Driven Detection techniques- ANN framework and LSTM framwork. It is infered that LSTM accuracies lie above ANN's which implies that is a better technique to detect symbols at the receiver side.



5 Conclusions

- This paper showed two Data driven approaches namely ANN and LSTM and proves that LSTM is better framework than traditional ANN because of LSTM's ability of storing memory elements. It gives significant increase in Accuracy and BER performance as well.
- To conclude, we can improve the channel model by including the vesicle theory and channel impulse response theory for passive receiver.Additionally, presence of enzymes will also contribute towards lessening of ISI and thus decreasing the BER.

6 Contribution of team members

6.1 Technical contribution of all team members

Muskan Matwani	**Naishi Shah**	**Yesha Shastri**	**Devshree Patel**	**Param Raval**
Mathematical Analysis of base article	New system model research	Analytical Graphs of base article	Mathematical Analysis of base article	Data generation ANN
Data generation of LSTM	Maths behind LSTM	Research on Diffusion rate and coefficient	Data generation ANN	ANN simulation
Analytical Graphs of base article	Research on enzymes	Maths behind LSTM	ANN simulation	Research on vesicles and channel impulse response
LSTM code with ANN comparison			Research on vesicles and channel impulse response	

6.2 Non-Technical contribution of all team members

Muskan Matwani	**Naishi Shah**	**Yesha Shastri**	**Devshree Patel**	**Param Raval**
Performance analysis of new contribution (3.2 LSTM)	Poster making	Motivation and Background	Performance analysis of new contribution (3.1 vesicle,CIR and enzymes)	Poster making
LSTM and ANN training analysis	Motivation	Performance analysis of base article	Inference for reproduced results	Introduction and Background
New contributions base article and LSTM	Performance analysis of base article	New contributions base article and LSTM	New contributions on removal of ISI	New contributions on removal of ISI
Adding reproduced and new results	Flow Diagram and system model design for LSTM	Conclusion	Conclusion	Bibliography
Problem solving and new framework	Design thinking	Presentation	Leadership and responsibility	Initiative and coordination

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