

Improved Channel Equalization using Deep Reinforcement Learning and Optimization

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Abstract

INTRODUCTION: Data transmission through channels observe large distortions arising due to the channel's dispersive nature challenged with inter-symbol interference.

OBJECTIVES: The paper serves twin tasks, firstly addresses the challenges of signal interference using RL based model and secondly evaluates its effectiveness using different communication channels.

METHODS: The author proposes an improvement in channel equalization with the implementation of Whale Optimization Algorithm (WOA) followed by the Q-Learning model for Reinforcement Learning (RL) to identify the most suitable bit streams that will offer least interference.

RESULTS: Simulation analysis is performed against four existing works in terms of Bit Error Rate (BER), reflecting 20 to 30% improvement. The performance evaluation is executed using AWGN, Rician, Rayleigh, and Nakagami channels to evaluate BER against SNR, Eb/No, and Es/No.

CONCLUSION: Overall, the proposed work offers high-speed data transfer through a reliable communication channel with least BER under different scenarios.

Keywords: Digital communication, Inter Symbol Interference (ISI), Channel equalization, Whale Optimization Algorithm (WOA), and Reinforcement Learning (RL).

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1. Introduction

Digital communication has been exponentially evolving since the last decade. It can also be described as a physical transfer of data to offer end-to-end communication. The communication system and data transfer have also been regularly engineered to provide a better communication environment. Akaiwa stated that telecommunication engineers study communication systems in parts to better understand and resolve issues related to robust data transfer whose major components are the transmitter, receiver, coders, and communication channel [1].

1.1 Inter Symbol Interference (ISI)

With time computation technology has been revolutionized and has given rise to Machine Learning based techniques to address specific communication channels. One of the major issues is Inter Symbol Interference (ISI) that arises due to overlapping of signals and leads to unreliable and noisy signals, as illustrated in Figure 1[2]. It results in distorted signals at the receiver's end instead of the original signal sent by the transmitter. This is what is known as ISI because the receiver receives a combination of signals across a time.

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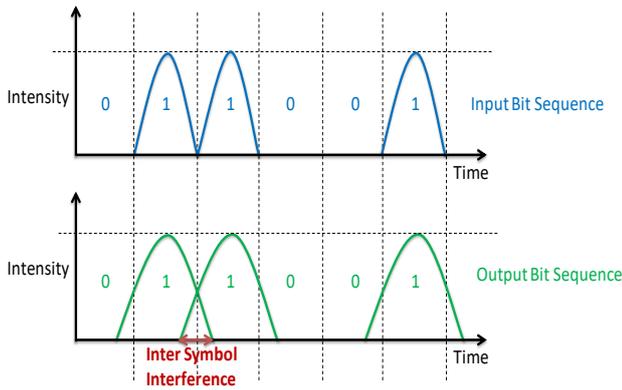


Figure 1. Inter Symbol Interference in digital communication

Numerous efforts in terms of algorithm and model development have been made to reduce and combat the challenging effects of interference. Suppose, set of the number of complex symbols that are being transmitted over a channel by a transmitter to the receiver. Then the signal is described as follows.

$$x \rightarrow [x_0, x_1, x_2, \dots, x_n] \tag{1}$$

Where represents each complex symbol in the signal. As a fact, each channel has its different characteristics. For instance, some of the channels may exhibit echos and some may exhibit a delay in transmission. However, practically most of the channels exhibit both characteristics. Echo is exhibited when the signal follows multiple paths to reach the receiver and is also called multipath channel and delay is exhibited when the channel is modeled as a delay line with each multipath signal modeled as a tap on the delay line. The following relationship denotes the signal when a multipath channel with characteristics that exhibit taps is transmitted through the channel that also inherits noise.

$$x_o = \sum_{i=0}^t c_i x_{o-i} + v_o \tag{2}$$

Where, x_0 is the 0th the complex symbol in x signal. At multipath characteristics ' c ' is stated as to have $t + 1$ taps.

$$c = [c_0, c_1, c_2, \dots, c_t] \tag{3}$$

Now, the corrupted signal due to ISI and noise that is received by the receiver is denoted as $x = [x_0, x_1, x_2, \dots, x_{n+t}]$. At this stage, equalization of the channel is performed to remove ISI and allow the receiver to obtain a signal with minimal ISI to meet real-world data transmission challenges [3].

The main concern here is that the data transfer should occur at high speed, however; high-speed data transmission is challenged by the reliability and incorporates interference and errors in data transfer. One solution to this is the involvement of larger bandwidth, which is practically impossible due to limited source availability [4]. Therefore, an alternate is to develop a good equalizer and train it to eliminate errors in data transmission.

1.2 Channel Equalization

It is the process that is dedicated to minimizing interference observed at the receiver end resulting in distorted signals. In digital communication design, channel equalization is performed just before the action of the channel decoder. Equalization is the process that a channel equalizer undergoes to overcome the issues of interference. Channel equalizers are also considered as the indispensable component of the communication system. The equalizer is highly dependent on the channel characteristics, and in the case of wireless communication channels, the channel characteristics vary with time due to the multipath fading effect. Under ideal conditions, the equalizer's output is considered equivalent to the deferred version of the transmitted signal. A generalized channel response following channel equalization is illustrated in Figure 2. Some of the various major types of equalizations performed to meet the data transmission requirements are discussed here.

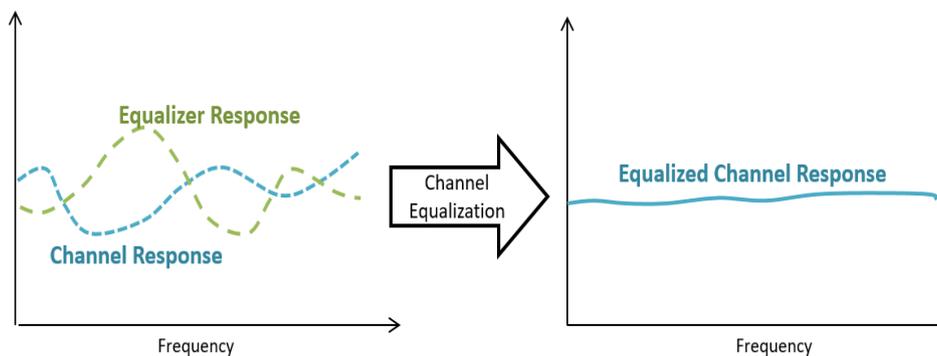


Figure 2. Channel responses after equalization

1.2.1. Linear Equalization

In this type of equalization, every channel is characterized by its equivalent discrete-time transfer function expressed in the time domain. Mathematically it is expressed as frequency response represents discrete time-frequency domain variable. Recently, unsupervised linear and non-linear channel equalization was performed by [5] to recover the signals transmitted over the noisy and linear ISI channel with improved error rates z . Here, the zero interference condition is met only when the transfer function sums into a nearly flat spectrum. Some of the popularly used linear equalizers are Zero Forcing (ZF) and Minimum Mean Square Error (MMSE).

1.2.2. Non-linear Equalization

The rising demand for data transmission has made the channels more crowded and results in the incorporation of inevitable noisy elements that result in distorted signals at the receiver side. Usually, equalizers are commonly employed to reduce these distortions and recover the signals. However, the linear equalizers' performance is found to be very poor and challenging when there exist multiple non-linear distortions. In such circumstances, non-linear equalizers are employed to attain the least Bit Error Rate (BER) and Mean Squared Error (MSE) which was not possible with the traditional linear equalization technique. In this context, Kari et al. had evaluated the effectiveness of the nonlinear channel equalization technique that proved to be highly efficient for acoustic communication with improved MSE [6]. Following this, Katwal et al. had taken advantage of adaptive filters for channel equalization that were improved based on Cuckoo Search (CS) optimization strategies followed by neural network architecture [7]. More recently, Majumder also implemented non-linear equalization based on the neural architecture that outperformed the traditional non-linear equalization technique with reduced BER [8]. Some of the non-linear equalization techniques are Decision Feedback Equalization (DFE), Maximum Likelihood Symbol Detection (MLSD) and Maximum Likelihood Sequence Estimation (MLSE).

1.2.3. Blind Equalization

This is the type of equalization technique based on the initial adjustment of the coefficients without the benefit of training. Therefore, they are also referred to as self-recovering or blind equalizers. They usually take advantage of adaptive equalizers without training to characterize the channel, and equalization is performed blindly without the reference signal's involvement. However, blind equalizers perform equalization that exclusively relies on the structure of the signal and its characteristics. Some of the blind equalization algorithms are Sato and Constant Modulus Algorithm (CMA). CMA was also implemented by Priyadarshi and Rai for blind channel equalization over standard signals to improve telecommunication strength. The work took advantage of CMA to offer fast signal transmission with reduced cost and error rates [9]. However, Nanda and Garg

had involved Moth Flame Optimization (MFO) to improve blind channel equalizer [10].

Table 1. List of Abbreviations

Abbreviation	Description
v_o	Noise
E_b/N_0	Energy per bit to noise power spectral density ratio
E_s/N_0	Energy per modulation symbol to noise spectral density
A-BER	Average Bit Error Rate
AWGN	Additive White Gaussian Noise
BER	Bit Error Rate
C	Channel
CMA	Constant Modulus Algorithm
CNR	Carrier-to-Noise Ratio
CS	Cuckoo Search
CSI	Channel State Information
dB	Decibels
DCSK	Differential Chaos Shift Keying
DFE	Decision Feedback Equalization
DL	Deep Learning
HP	High Priority
ISI	Inter Symbol Interference
L-BER	Logarithmic Bit Error Rate
LP	Low Priority
MIMO	Multiple-Input and Multiple-Output
MLSD	Maximum Likelihood Symbol Detection
MLSE	Maximum Likelihood Sequence Estimation
MMSE	Minimum Mean Square Error
MSE	Mean Squared Error
OFDM	Orthogonal Frequency-Division Multiplexing
PSO	Particle Swarm Optimization
RL	Reinforcement Learning
SI	Swarm Intelligence
SNR	Signal-to-Noise Ratio
SOHS	Second Order Hybrid System
vs.	Versus
WOA	Whale Optimization Algorithm
ZF	Zero Forcing
x	Digital Signal

One of the many approaches to address the challenges of interference is to train the system using the channel model followed by the fine-tuning of the receiver with known data with Deep Learning (DL) approaches [11]. However, this approach's limitation is the suboptimal training at the transmitter end which results in unsatisfactory response. Another solution offered by various researchers is supervised training of auto encoders [12]. However, no practical implementation had been demonstrated to offer real-time application. Recently, an alternate training approach has been proposed by researchers in which auto encoders were alternately trained using supervised learning at the receiver end and reinforcement training at the transmitter end [13].

Additionally, the deep learning scheme has also attracted researchers for channel estimation [14] along with feedback of Channel State Information (CSI) in the case of Multiple-Input and Multiple-Output (MIMO) channels [15]. Reinforcement learning has been widely used to resolve decision-making in numerous applications ranging from vehicle navigation control to power management in buildings [16]. However, limited research has been found in the field of communication environments.

In the present work, end-to-end learning of the communication system is performed. WOA has been implemented to optimize the channel equalizer followed by the Q-learning model for reinforcement learning to offer a high-speed data transfer with a minimal error rate and interference. The proposed model is further evaluated in terms of Bit Error Rate (BER) and Signal-to-Noise Ratio (SNR) against various communication channels.

1.3. Contribution of the paper

The paper presents twofold efforts. Firstly, a reinforcement learning-based model with optimized channel equalization is developed that could successfully address interference issues. In this research work, the concept of WOA is implemented as an optimization technique with reinforcement learning to reduce channel equalization issues. Secondly, the performance of the proposed model has empirically evaluated terms of BER under different SNR levels.

1.4. Organization of the paper

The paper starts by introducing data transmission over communication channels with the potential challenges that lead to the incorporation of errors in data transfer. Section 2 summarizes the state of artwork about channel equalization to resolve interference issues. Section 3 describes the proposed model and its salient features and Section 4 is dedicated to performance analysis and empirical evaluation. Section 5 shares the paper's concluding remarks followed by the list of references communicated in the paper.

2. Literature Review

The issue related to signal interference has posed a growing challenge and has become an indispensable part of the modern digital communication system. Researchers have implemented numerous strategies to resolve ISI with the adoption of nature-inspired optimization, the involvement of adaptive filters, and various machine learning techniques. This section covers some of the most distinguishing works proposed to exhibit minimal signal distortions at the receiver end. Lin et al. (2011) proposed a model based on a self-evolving neural fuzzy interference network and combines orthogonal polynomials and linear functions. They had implemented evolutionary reinforcement learning a variant of RL to deploy a structure that was used for computing fuzzy rules and parameter learning for parametric adjustment. Cooperative particle swarm optimization was also involved in the design to improve global search ability and neural learning [17]. Ye et al. (2017) had considered a communication system as a black-box and implemented deep learning schemes to improve end-to-end signal transmission. The issues that arise due to channel distortion were addressed using deep learning models first trained offline against the data obtained from the simulation analysis based on the channel statistics followed by the online mode against the transmitted data. Experimentation performed about the Orthogonal Frequency-Division Multiplexing (OFDM) system established that deep learning proved to be better than the existing approaches in terms of BER evaluation with SNR ranging to 30dB. However, work lacks rigorous and comprehensive analysis for better performance in real-time application [18]. Bai et al. (2019) had recognized the application of the simplest matched filter to avoid multipath propagation and enhance SNR in a chaotic communication. It is acknowledged that chaotic communication is bestowed with a broadband frequency spectrum that significantly challenges conventional wireless communication system applications. In this scenario, Second Order Hybrid System (SOHS) was used to create chaos that was addressed by DCSK based communication. The SOHS-DCSK generated an additional bit stream that was capable of precisely encode information even in the presence of chaotic signals. It offered reliable data transmission with High Priority (HP) bits transmitted at a low transmission rate while Low Priority (LP) bits were transmitted at a higher transmission rate. Compared to DCSK, SOHS-DCSK demonstrated a higher data transmission rate with signals compatible with conventional antennas and transducers [19]. Cheng et al., (2019) had designed a deep learning scheme for channel estimation followed by equalization. In the proposed scheme, information of channel state is gathered by deep learning of neural networks followed by equalization of distorted frequency signals to compute information regarding bits. Simulation studies established that deep learning-based schemes outperformed the conventional schemes for BER against variable SNR values [20]. Bai et al. (2020) proposed an M-ary Differential Chaos Shift

Keying modulation through Chaotic Shape-forming Filter (CSF-M-DCSK) to transmit sub-streams with variable performances. Best noise performance was achieved when signals were modulated using a chaotic shape filter and demodulated using the maximum likelihood decision rule. In contrast to the DCSK concept, the proposed modulation strategy proved to successfully resolve multipath performance and noise reduction with higher data transmission rates. Simulation analysis in AWGN and similar channels had shown that proposed CSF-M-DCSK outperformed in terms of BER with proven feasibility in real scenarios [21]. Majumder and Giri (2020) had proposed an improvement in the training of neural network-based equalizers using the architecture of Particle Swarm Optimization (PSO). The involved strategy proved to successfully optimize the translation of weights in the hidden layer of neural network architecture that significantly improved the BER of the proposed architecture. The superiority of the training strategy was also established as compared to the existing equalization schemes in terms of BER [22]. Katwal and Bhatia (2020) had addressed the ISI as the issue of digital data transfer. They found that the error rate was highly dependent on the channel estimation and the process of equalization. Therefore, the authors had designed a method to optimize the channel data using Cuckoo Search Optimization (CSO) to improve ISI. The data-optimized through CSO was cross-validated using neural network architecture. Simulation analysis in terms of Average-BER and Logarithmic-BER demonstrated an overall improvement of 30% to 50% as compared with existing approaches [7]. Zhang and Yang (2020) presented a Machine Learning (ML) architecture based channel equalization inspired by the deep learning neural networks. A DL-based neural network followed a comprehensive overview of various equalizers for channel equalization. The work was evaluated for the OFDM system, demonstrating the better BER performance of deep learning architecture over variable SNR levels ranging from 5dB to 30dB as compared to existing machine learning techniques [23]. Ji et al. (2020) had postulated an approach to address interference in multipath propagation using a blind equalization based on Deep Learning (DL) architecture. The approach exhibited two modules, one representing blind equalization and the other representing DL taking advantage of ResNet structure. Compared to traditional DL approaches, the proposed DL that took advantage of blind equalization proved to offer 30% improvement in high SNR and extensive multipath scenarios. Additionally, it also reduced the requirement of large training data for evaluation purposes [24].

3. Methodology

The proposed work aims to minimize the ISI and signal distortions while improving the existing equalizers when signals are retrieved at the receiver end. The designed module is further divided into two main blocks:

- Swarm Intelligence (SI) block
- Deep Learning (DL) block

The conventional communication process comprises a transmitter that sends the signal and the receiver where the transmitted signal is received. However, between these two, number events can be well understood in terms of processes that involve encoders-decoders and the communication channel. The positioning of the two blocks in the communication process is further illustrated in Figure 3(a).

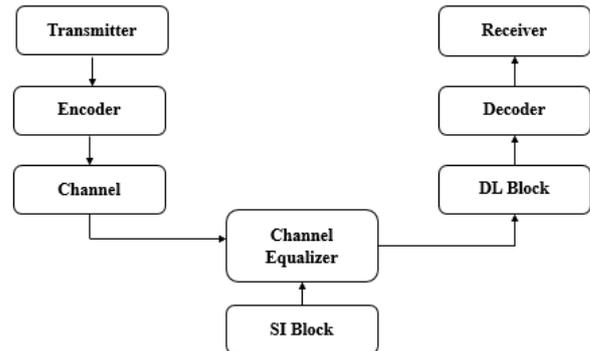


Figure 3(a). Block diagram of the proposed model

To overcome the ISI issues, channel equalizers have been introduced to the communication models. However, the issue of signal interference still exists and remains an open area of research. In the proposed work authors had introduced SI block that tried to improve the channel equalization. In SI block, Whale Optimization Algorithm (WOA) is used as the swarm intelligence technique where the channel equalizer is first enhanced with the involvement of WOA for identifying the least interference signals. This is followed by implementing RL architecture in DL block to cross-validate the signals retrieved using SI block that most closely represents the initially transmitted signal. Finally, evaluation in terms of BER and SNR over a number of simulations is performed.

3.1. Swarm Intelligence (SI) block

SI is a nature-inspired algorithm that is based upon the behavior collection of different species like fishes, mammals, insects, etc [25]. Many researchers focussed upon some new nature-inspired metaheuristic algorithms that are; Whale Optimization Algorithm, Ant Lion Optimizer, Butterfly Optimization Algorithm, and sine cosine algorithm [26]. In a swarm, intelligence-based algorithm swarms are the agents that interact with another swarm into the environment [27]. Conventionally, ISI can be minimized with channel equalization performed just before decoding the signals at the receiver end, as also discussed in Section 2. Various researchers have involved the concept of swarm intelligence to address the

equalization issues of channel equalizers. Some researchers took advantage of particle swarm architecture using Particle Swarm Optimization (PSO) [28]. While others were inspired by the behavioral characteristics of Firefly [29], Cat [30], and Cuckoo [7]. Whale Optimization Algorithm (WOA) developed by Mirjalili and Lewis has recently stepped into the swarm intelligence category and was inspired by whales' behavior [31]. More recently, a comprehensive survey had established that WOA had shown potential applications in addressing the optimization issues in a much better way [32]. In recent years, SI is also used for optimization in wireless networks [33]. Various applications of SI are image segmentation, pattern recognition, intelligent transportation system, wireless sensor networks, etc. In the current scenario, SI is applied to solve real-world problems related to various fields like healthcare, finance, marketing, research, etc.

3.1.1. WOA Algorithm

Swarm Intelligence (SI) is a natural behavior-inspired algorithm series that mimics the characteristics of nature's elements. The literal meaning of Swarm is group, and the fitness function is dependent upon group behavior. This paper utilizes the WOA algorithm to reduce the symbol interference. The algorithm consists of two phases:

1. Exploitation phase: In this phase, whales follow a spiral path to encircle the prey as illustrated in Figure 3(b).
2. Exploration phase: In this phase, the prey is randomly searched by the whales.

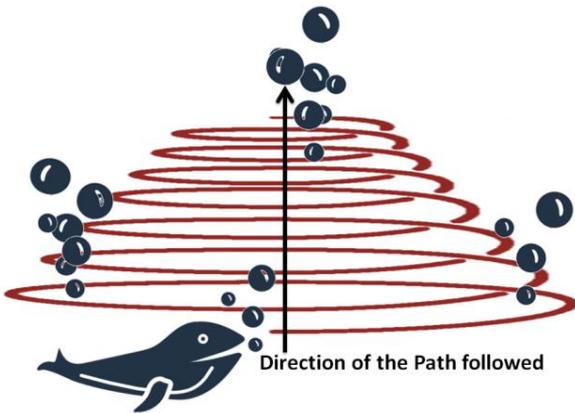


Figure 3(b). Whale Optimized Algorithm inspired by the behavior of Whales

A mathematical explanation of Exploitation Phase
 Prey encircling: Whales are found to locate the prey and follow a spiral path to encircle them. Encircling prey works on two assumptions,

- Firstly, it considers that the target prey is the prime candidate for achieving the most favorable solution.
- Secondly, the other search intermediaries' care assumed to change their positions regarding the search agent continuously. The following equations also represent this behavior:

$$P_{w(i_{tr}+1)} = P_{p_{itr}} - A_{coeffvect} * D_{vect} \tag{4}$$

$$D_{vect} = |B_{coeffvect} * P_{p_{itr}} - P_{w_{itr}}| \tag{5}$$

Where $P_{p_{itr}}$ is the whale's last position at iteration 'itr' also corresponding to the prey position, $P_{w(i_{tr}+1)}$ is the whale's present position, the distance between prey and whale is represented by D_{vect} . $A_{coeffvect}$ and $B_{coeffvect}$ are coefficient vectors that are further computed as follows:

$$A_{coeffvect} = 2 * A_{vect} * rnd_{vect} - A_{vect} \tag{6}$$

$$B_{coeffvect} = 2 * rnd_{vect} \tag{7}$$

Here, rnd_{vect} represents random values between 0 and 1. The search space is governed by A_{vect} and to shrink the search space analogous to the spiral path followed by the whale, the value of A_{vect} is decreased linearly from 2 to 0 over the number of iterations that decrease the oscillating range of $A_{coeffvect}$. Finally, a random selection of value for $A_{coeffvect}$ in the range of -1 and +1 will result in a new position.

Updating Spiral path Position: Let us consider the whale position coordinates as (P_w, Q_w) and prey position coordinates as (P_p, Q_p) . The spiral path followed by the whales is represented as follows:

$$P_{w(i_{tr}+1)} = exp^{CV} * cos(2\pi V) * D_{p_{vect}} + P_{p_{itr}} \tag{8}$$

$$D_{p_{vect}} = |P_{p_{itr}} - P_{w_{itr}}| \tag{9}$$

The logarithmic shape of the spiral is represented as the random variable that lies between -1 and +1. In most of the cases there are 50% chances that it involves a shrinking encircling or spiral mechanism. The selection is done as follows:

$$P_{w(i_{tr}+1)} = \begin{cases} P_{p_{itr}} - A_{coeffvect} * D_{vect} & \text{if } R < 0.5 \\ exp^{CR} * cos(2\pi R) * D_{p_{vect}} + P_{p_{itr}} & \text{if } R \geq 0.5 \end{cases} \tag{10}$$

A mathematical explanation of Exploration Phase

The exploration phase that represents the search phase determines the search agent's position in respect to the randomly selected search agents irrespective of the best search agent determined in the process. The implemented mechanism corresponds to the strengths of WOA to deal with the shortcoming associated with the local optimization problems. The following equations further represent the model.

$$P_{w(i_{tr}+1)} = P_{w_{rand}} - A_{coeffvect} * D_{vect} \tag{11}$$

$$D_{vect} = |B_{coeffvect} * P_{w_{rand}} - P_{w_{itr}}| \tag{12}$$

Where $P_{w_{rand}}$ represent the position of a random whale within the population Inspired with these facts, swarm intelligence technique, specifically, WOA has been implemented in the proposed SI block to improve channel equalizer performance involved in data transmission. The steps involved in optimizing the channel equalizer are summarized in Algorithm 1.

Algorithm 1: Optimization using WOA

1. Input: B_{stream} // Bit Stream
2. Output: OB_{stream} // Optimized Bit Stream
3. Initialize WOA parameters:
4. Itr // Search agents,
5. L_{B_N} // lower bound of "N" variables

6. U_{B_N} // upper bound of “N” variables
7. f_{fit} // fitness function
8. Calculate: $T = \text{size}(B_{\text{stream}})$ // size of the input
9. For each i_{value} in T
10. Calculate: $B_{\text{stream}_{\text{selected}}} = \sum_{i=1}^T B_{\text{stream}}(i_{\text{value}})$
// value for selected B_{stream} in terms of N
11. Calculate:
$$B_{\text{stream}_{\text{th}}} = \frac{\sum_{i=1}^T B_{\text{stream}}(i)}{\text{Length}(B_{\text{stream}})}$$
 // $B_{\text{stream}_{\text{th}}}$ is the threshold which should be achieved by supervisor N with respect to B_{stream}
12. Call WOA fitness function
13. $f_{fit} = \begin{cases} \text{False, } B_{\text{stream}_{\text{selected}}} < B_{\text{stream}_{\text{th}}} \\ \text{True, } B_{\text{stream}_{\text{selected}}} \geq B_{\text{stream}_{\text{th}}} \end{cases}$
14. Calculate: $\text{Opt}_{\text{value}} = \text{WOA}(f_{fit}, N, L_{B_N}, U_{B_N})$
15. End_for
16. While $\text{Itr} \neq \max(T)$
17. Assign: $\text{New}B_{\text{stream}} = \text{Opt}_{\text{value}}$ // store WOA optimized B_{stream} values
18. End_while
19. Return: $\text{OB}_{\text{stream}} = \text{optimize}(\text{New}B_{\text{stream}})$ // optimized B_{stream}

The above algorithm analyses the input bit stream B_{stream} using WOA descriptors. Following this step threshold bit stream is determined as $B_{\text{stream}_{\text{th}}}$ for optimizing equalizer to minimize signal interference. Based on this threshold value of bit stream are selected and fitness function employed to compute an optimal bit stream value $\text{Opt}_{\text{value}}$. Finally, in an iterative manner, WOA returns-optimized bit stream $\text{OB}_{\text{stream}}$ as a result of channel equalization.

Fitness function and Parametric Value of WOA

$$f_{fit} = \begin{cases} \text{False, } B_{\text{stream}_{\text{selected}}} < B_{\text{stream}_{\text{th}}} \\ \text{True, } B_{\text{stream}_{\text{selected}}} \geq B_{\text{stream}_{\text{th}}} \end{cases}$$

Two parameters are passed $B_{\text{stream}_{\text{selected}}}$, $B_{\text{stream}_{\text{th}}}$ where $B_{\text{stream}_{\text{selected}}}$ is represent current bitstream from a set of bit stream and $B_{\text{stream}_{\text{th}}}$ represents mean of a set of bit stream that is considered as a threshold value.

3.2. Deep Learning (DL) block

When WOA is applied on the bitstream then it returns an optimal set of the bit stream that is considered as an input of the Deep Learning and we got a minimum interference during communication. The present block also depicted in Figure 3(a) represents Reinforcement Learning (RL) architecture as a computational intelligence technique. In the RL approach, states, action, and reward are the main determinant factors. The RL agents are considered wiser enough to determine the action in a state to take full advantage of the reward ([34, 35]). The rewards are used as feedback to agents to generate experience. According to the technical justification initially given by Watkins and Dayan, with the increase in the learning experience, the RL agent learns to make the best or the optimal decision to

maximize the benefits [36]. Q-learning is a type of model-free RL technique in which the defined agents are rewarded in the next step to evaluate the previous step's actions. Q-learning was evaluated by Dirani et al. in autonomies and self-organizing Radio Access Networks to offer higher spectral efficiencies at a considerably lower operational cost [37]. More recently, Niu et al. had employed Q-learning to detect new network attacks while monitoring the deformity in the state vector due to attack. It was demonstrated that the technique proved to be very effective in terms of Q-function estimate error and packet dropped [38]. In the present DL block, Q-learning is used for deep learning of the system to offer channel equalization to offer minimal signal interference. A generalized Q-learning architecture is illustrated in Figure 4. In Q-learning, for every pair of action at a particular state 's', a reward 'r' is determined. Here, Q-value is the action-value function that depends on two inputs, state 's' and action 'a' in that state and returns a future reward as expected due to action 'a'.

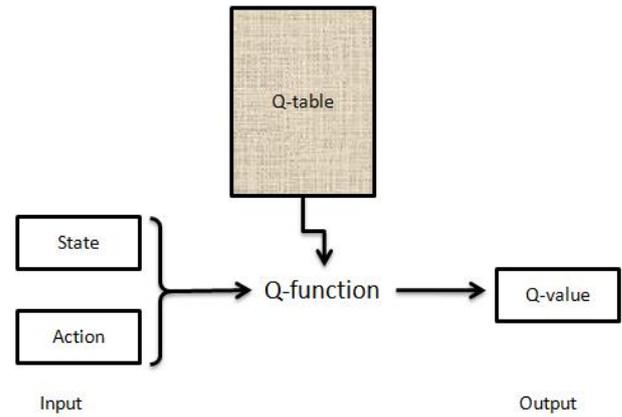


Figure 4. Q-learning

Mathematically, it is denoted as $Q(s, a)$.

$$Q(s, a)_{\text{new}} = Q(s, a) + \alpha [r(s, a) + \gamma \max_{a'} (Q(s', a')) - Q(s, a)] \quad (13)$$

Where, $Q(s, a)_{\text{new}}$ is new Q-value, $Q(s, a)$ is the current Q-value, $r(s, a)$ reward granted for state s against action a , $\max(Q(s', a'))$ is the maximum expected future reward with α and γ as learning and discount rates, respectively..

In Q-learning, the Q-function analyses Q-table rows for a particular state and columns for the matching actions to return the corresponding Q-value, which is also labelled as future reward. Here, RL agent selects the action that represents the highest Q-value after learning from the Q-table that represents channel and equalizer response. The Q-learning algorithm selects the most appropriate actions based on Boltzmann policy [39], greedy policy, or ϵ -greedy

[40]. The employed Q-learning steps in the DL block are given in Algorithm 2.

Algorithm 2: Q-learning Algorithm for Deep Learning

1. Input: $OB_{stream} \rightarrow$ Optimized Bit Stream
 2. Output: $B_{stream_{best}} \rightarrow$ Bit Stream with minimal interference and performance_{parameters}
 3. Initialize Q-learning parameters
 4. $\alpha \rightarrow$ Learning rate
 5. $\gamma \rightarrow$ Discount rate
 6. $R \rightarrow$ Reward matrix
 7. For_{each} bit in OB_{stream}
 8. Select state randomly //select a state value randomly
 9. For_{each} s in state
 10. a \rightarrow policy(s) //Select an action a using Boltzmann or ϵ -greedy policy
 11. r \rightarrow obtain for a from R // obtain reward r for action a from reward matrix R
 12. s' \rightarrow next state // moved on to the next state
 13. Update the Q(s, a) for current state
 14. $Q(s, a)_{new} = Q(s, a) + \alpha[r(s, a) + \gamma \max(Q(s', a')) - Q(s, a)]$ //update Q-values
- Where, $Q(s, a)_{new} \rightarrow$ is new Q-value, $Q(s, a) \rightarrow$ is the current Q-value, $r(s, a) \rightarrow$ reward granted for state s against action a, $\max(Q(s', a')) \rightarrow$ maximum expected future reward
15. Update state s with s' until s' = max (state)
 16. End_{for}
 17. Show states with highest reward as $B_{stream_{best}}$
 18. Calculate performance_{parameters}
 19. End_{for}
 20. Return: $B_{stream_{best}} \rightarrow$ least interference bit stream and performance_{parameters}

Q-learning determines the reward for each state that performs equalization of the input OB_{stream} . Based on this reward most suitable bit stream is determined for signal communication that is considered to offer least interference. The performance_{parameters} corresponding to this most suitable $B_{stream_{best}}$ are returned in the DL block using Q-learning and are further evaluated to determine the proposed channel equalization design's performance.

4. Results

In this section, the outcomes of the simulation analysis of the proposed channel equalization strategy are summarized in terms of BER using multiple communication channels, namely, AWGN, Rician, Rayleigh, and Nakagami channels. In addition to traditional BER evaluation against variable SNR levels, a more comprehensive analysis is involved in the proposed work in which BER is also expressed as Carrier-to-Noise Ratio (CNR) that is expressed as energy per bit to noise power spectral density ratio (E_b/N_0) and energy per symbol to noise power spectral density ratio (E_s/N_0). The simulation of the results

is based on randomly generated data for performance analysis of the proposed system.

4.1 Performance evaluation in AWGN channel

The performance of the proposed equalization strategy is first evaluated in the AWGN channel in terms of BER evaluation. Figure 5 shows the comparison of BER exhibited by the proposed work against [21], Kalman filter [41], [42], and [19] work against variable SNR levels. The plot of BER against SNR expressed in dB shows that an average BER of the proposed work is 0.031, Katwal and Bhatia work is 0.84, Kalman is 0.75, Bai et al. is 0.64 and 0.46. This shows that the proposed work exhibited the least BER among all the studies.

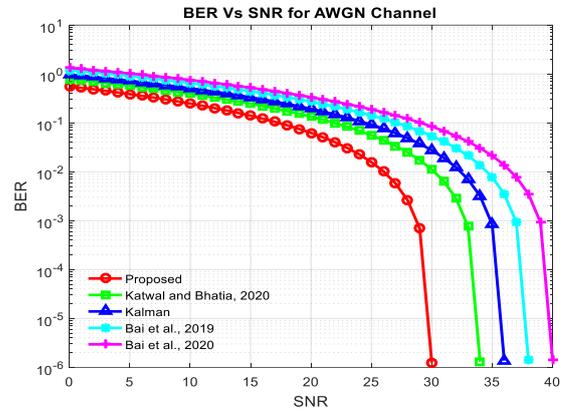


Figure 5. BER vs. SNR analysis in AWGN channel

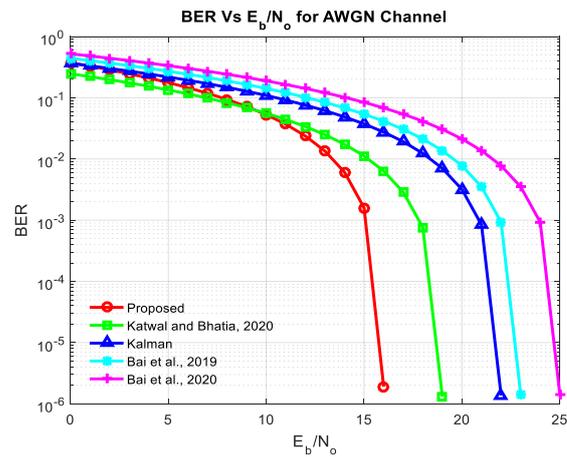


Figure 6. BER vs E_b/N_0 analysis for AWGN channel

Figure 6 shows that the proposed work exhibits higher BER at lower values of E_b/N_0 which gets improved with the increase in E_b/N_0 . This shows that better BER performance is observed for the proposed work between 10 and 17 E_b/N_0 while exhibiting an average BER of 0.87 as compared to existing works.

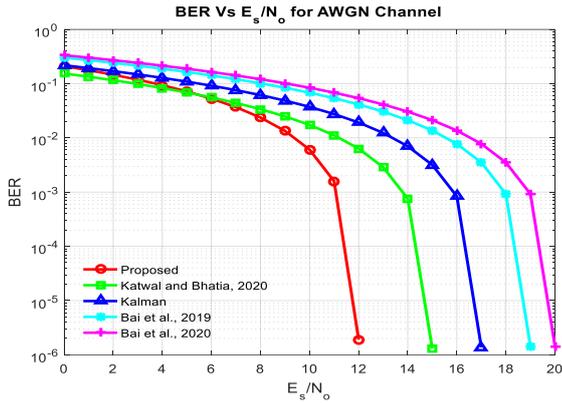


Figure 7. BER vs. E_s/N_0 analysis for AWGN channel

Next, BER is evaluated against the energy per symbol to noise spectrum in Figure 7 which plots the simulation analysis of BER performance demonstrated by proposed and existing studies against variable E_s/N_0 values. In this case, it is observed that the proposed work outperformed the existing studies with the least average BER of 0.85.

4.2 Performance evaluation in Rician channel

In this sub-section BER performance of the proposed work is further evaluated in the Rician channel. In the process, the exhibited BER is compared with the existing work of Katwal et al.2020, Kalman, and Bai et al.

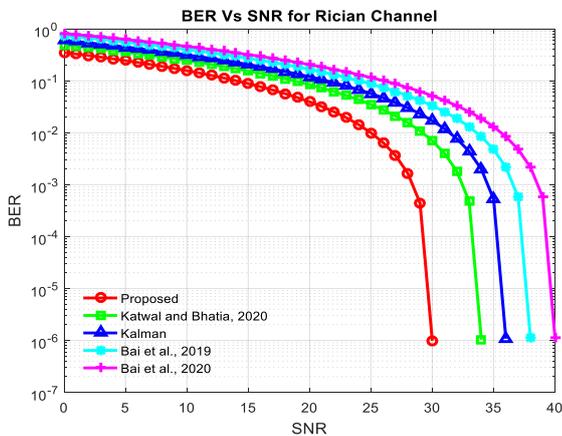


Figure 8. BER vs. SNR analysis for Rician channel

The observed BER values are plotted against variable SNR values in Figure 8, evaluating communication success using the Rician channel. It is observed that BER decreases with an increase in SNR values for all the studies. However, the least average BER of 0.91 is kept for the proposed work illustrated with red color in Figure 8.

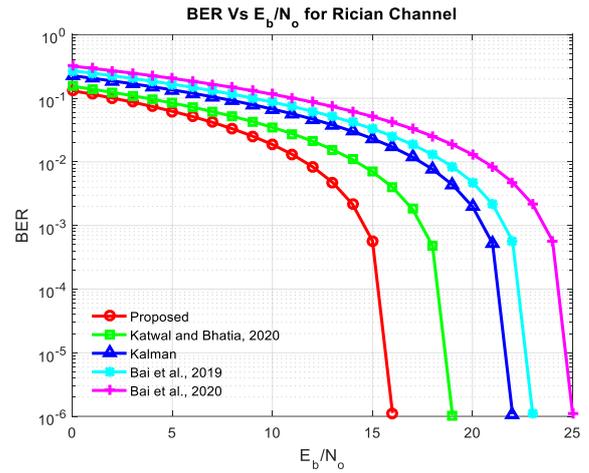


Figure 9. BER vs. E_b/N_0 analysis for Rician channel

Figure 9 further evaluates the effectiveness of the proposed work in terms of BER evaluated against variable energy per bit to noise ratio represented as E_b/N_0 . In the case of Rician channel-based communication, the proposed work demonstrated the least BER with an average value of 0.034 as compared to 0.027 by [21], 0.023 by Kalman, 0.019 and 0.015 by Bai et al. work [42, 19]

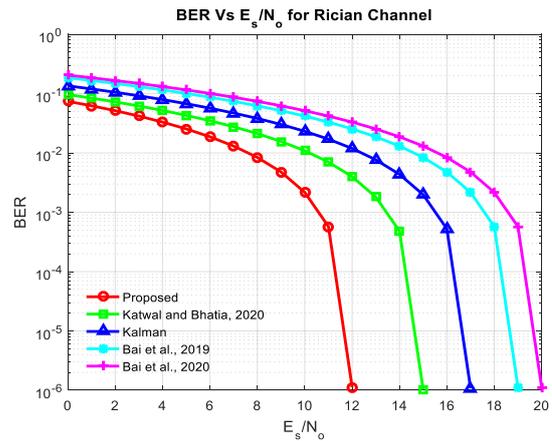


Figure 10. BER vs. E_s/N_0 analysis for Rician channel

BER evaluation against energy per symbol to noise spectral density using the Rician channel for communication is represented in Figure 10. It is observed from the graph that the proposed work again outperformed the existing works while achieving an average BER of 0.056.

4.3 Performance evaluation in Rayleigh channel

Rayleigh fading channel environment is also employed for evaluating the performance of the proposed channel equalization work to design a least interference-based communication system. Figure 11 presents a graphical comparison of the BER in the Rayleigh channel. The graph

illustrates that the proposed work exhibits an average BER of 0.064 while the lowest among the existing studies exhibit an average BER of 0.046, 0.032, 0.023, and 0.018 by [19], Kalman and [42, 19] work.

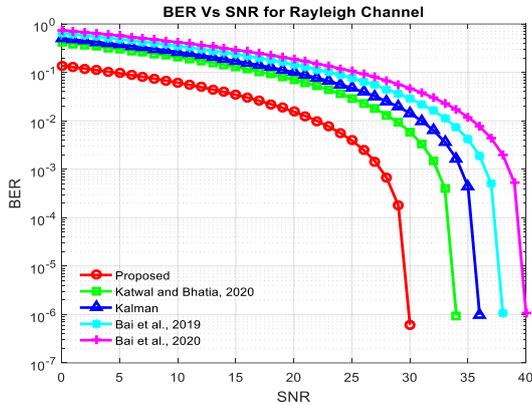


Figure 11. BER vs. SNR analysis for a Rayleigh channel

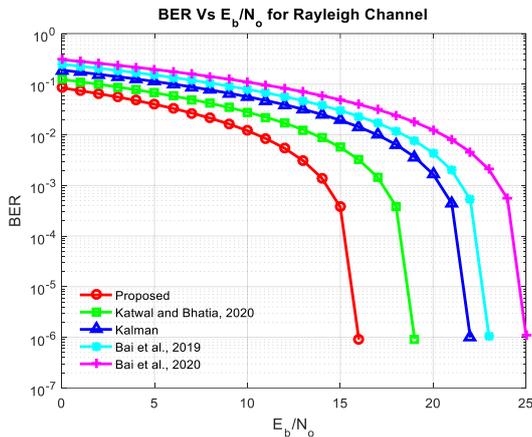


Figure 12. BER vs. E_b/N_0 analysis for a Rayleigh channel

Figure 12 represents the BER analysis against energy per bit to noise ratio to evaluate the communication systems in the Rayleigh channel. It is observed that all the works are very sensitive to lower E_b/N_0 values and exhibits large BER. However, at higher E_b/N_0 values, the proposed work outperformed the existing works with an average BER of 0.072.

Further, Figure 13 represents that the BER analysis against energy per symbol to noise ratio also followed a similar trend and exhibits the lowest average BER of 0.086 in comparison to the existing works to offer the least interference-based communication. In other words, evaluation of BER illustrates that the proposed work again outperforms the existing works even in the case of the Rayleigh fading channel.

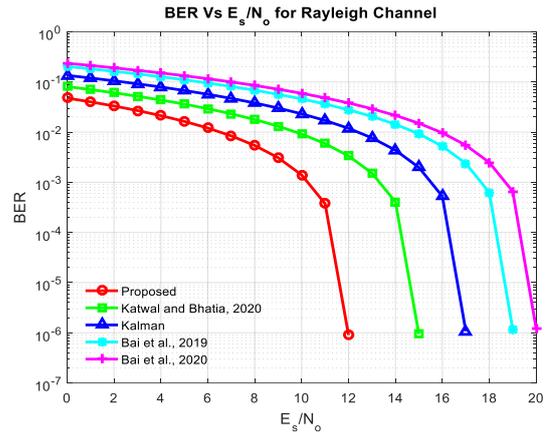


Figure 13. BER vs. E_s/N_0 analysis for a Rayleigh channel

4.4 Performance evaluation in Nakagami channel

Literature had shown that researchers had employed Nakagami channels to evaluate multipath communication. For instance, Dawa et al. had considered BER of DS-SS in Nakagami channel [43], while [44] had employed Nakagami channels for BER performance over m-Nakagami fading channels [44]. In a similar scenario, the authors also evaluated their proposed work using a multipath Nakagami channel to offer the least interference-based communication system in terms of BER.

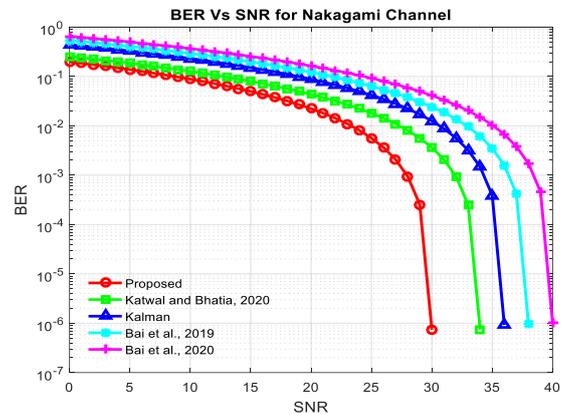


Figure 14. BER vs. SNR analysis for Nakagami channel

The computed BER at various SNR levels is illustrated in Figure 14 for proposed as well as the existing works of [21], Kalman and ([42, 19]). It has been observed that overall the SNR levels the proposed work exhibit the least BER with an average value of 0.038. Similar observations have also been drawn when BER is evaluated against E_b/N_0 and E_s/N_0 as shown in Figure 15 and Figure 16, respectively.

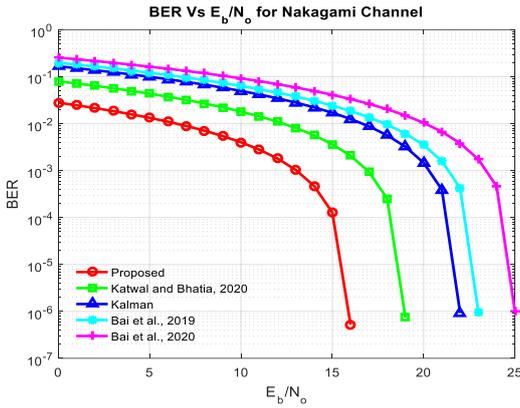


Figure 15. BER vs. E_b/N_0 analysis for Nakagami channel

BER evaluation against E_b/N_0 Figure 15 shows that the proposed work demonstrates an average BER value of 0.093, followed by 0.086 [21], 0.73 (Kalman), 0.54 (Bai et al., 2019), and 0.41 (Bai et al., 2020) by the existing works.

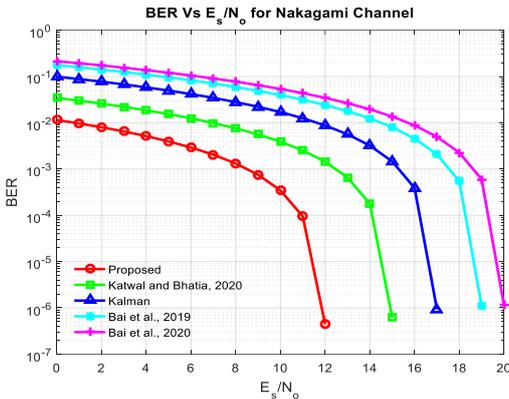


Figure 16. BER vs. E_s/N_0 analysis for Nakagami channel

Further, Figure 16 shows that an average BER of 0.0024, 0.0004, 0.0097, 0.086, and 0.079 is exhibited by the proposed work (Katwal and Bhatia 2019), Kalman and (Bai et al.2019; Bai et al. 2020) works, respectively. In other words, the proposed work outperforms the existing results with an average BER of 0.093 and 0.0024 in the case of communication performed using Nakagami fading channel when BER is evaluated against energy per bit to noise ratio and energy per symbol to noise ratio, respectively.

In the current scenario, channel equalization is a demanding topic for the research area. Various applications of the proposed work are system communication, adaptive control, adaptive filtering for signal processing, signal pattern recognition, and numerous cases in medical and other scientific researches.

5. Conclusions

In the present work, the authors had addressed the issue of signal interference inherited in the communication system.

The authors had proposed a multi-block architecture to improve the channel equalizer with the implementation of WOA in the SI block followed by a DL block that implements Q-learning to recognize the best bit streams that would offer the least interference data transmission. The effectiveness of the proposed is evaluated by BER while using different communication channels, namely, AWGN, Rician, Rayleigh, and Nakagami channels. The performance evaluation of the proposed work against existing work exhibits highly reliable data transmission reflected by a comparative analysis of BER versus SNR, E_b/N_0 and E_s/N_0 against the four existing works. Overall, the proposed work offers a reliable data transmission over various communication channels with the least BER. Thus, the article presents how researchers can utilize different nature-inspired optimization techniques for improved channel equalization to address signal interference challenges. In future, the proposed model will be based on a dataset oriented for model training that helps to minimize the BER as well as reduce channel interference. The model will be cross-validated by utilizing another classifier with reinforcement learning as a deep learning mechanism.

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