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Research Article

Optimizing Nonlinear Distortion and Interference in MC-CDMA Receivers Employing Deep Neural Networks

C. V. Ravikumar,[1] **Kalapraveen Bagadi**,[2] **K. Rushendrababu**,[3] **Asadi Srinivasulu**,[4] **and Satish Kumar**[1]

[1]*School of Electronics Engineering, Vellore Institute of Technology, Vellore 632014, India*
[2]*School of Electronics Engineering, VIT-AP University, Amaravati, Andhra Pradesh 522237, India*
[3]*SR Gudlavaleru Engineering College, Gudlavaleru, AP, India*
[4]*IT & Head Research, Data Science Research Lab, BlueCrest University, Liberia 1000, South Africa*

Correspondence should be addressed to Asadi Srinivasulu; head.openlabs@bluecrest.edu.lr

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Systems that employ multicarrier code division multiple access, commonly known as MC-CDMA, produce outstanding results in terms of both the performance of the system as a whole and the efficiency with which it uses the spectrum. However, multiple access strategies are susceptible to interference despite their high spectrum efficiency. This work aims to reduce multiple access interference (MAI) by developing an MC-CDMA receiver. When MC-CDMA deteriorates nonlinearly, standard receivers, namely, zero forcing (ZF), maximal ratio combining (MRC), minimum mean square error (MMSE), and equal gain combining (EGC), are unable to cancel MAI. Neural network (NN) receivers are a better option due to their nonlinear nature. Based on the simulation results, the suggested deep neural network- (DNN-)based schemes outperform the current baselines in terms of error handling and usability. This research explores the viability and effectiveness of a DNN-based receiver designed for MC-CDMA with nonlinearity degradations. The focus of this research is on MC-CDMA.

1. Introduction

The multicarrier (MC) technique has widespread application in fifth generation (5G) and beyond systems that utilize the concept of orthogonal frequency division multiplexing (OFDM). The technique known as multicarrier modulation (MCM) is widely used in various wireless networks, including the third generation partnership project (3GPP), next-generation wireless fidelity (Wi-Fi) 6 and Wi-Fi 6E systems (IEEE 802.11ax), and cellular vehicle-to-everything (C-V2X) standards. To achieve a reasonably constant fading rate, the data stream being communicated is typically segmented into multiple substreams by several MC systems. These substreams are then transmitted across parallel narrowband subchannels. OFDM-based multipath cancellation is an essential tool for both the current and future generations of wireless systems. Affordable receivers can effectively mitigate problems associated with multipath fading, including delay spreading and intersymbol interference (ISI). The data stream being transferred is typically segmented into multiple substreams by many MC systems [1, 2].

Over the past few years, research has been conducted on advanced MC approaches that utilize OFDM to enhance dependability, spectrum efficiency, and energy efficiency. The OFDM method of broadband multicarrier modulation splits a signal into a large number of orthogonal narrowband channels, making it resistant to intersymbol interference (ISI) [3, 4]. Another technique, called direct sequence code division multiple access (DS-CDMA), utilizes spread spectrum technology to enable multiple devices to share the same bandwidth while transmitting information [5]. DS-CDMA has the potential to increase the overall system capacity. Recognizing the individual benefits of both strategies, combining CDMA and OFDM has been proposed to leverage the advantages of both approaches. This combined approach is known as the MC-CDMA system in technical circles.

However, similar to other multiple access techniques, MC-CDMA is susceptible to multiple access interference (MAI) within the same cell, particularly when multiple users share the same cell. Therefore, it is essential to have a receiver capable of accurately detecting users while minimizing MAI [6]. In [7–9], a new spreading matrix based on the rotating Walsh–Hadamard spread OFDM was presented as a solution to address this challenge.

According to [10], when low-complexity detection techniques such as minimal mean squared error (MMSE) are used, S-OFDM outperforms its predecessor, S-OFDM, in terms of overall performance. In a similar vein, [11] introduced a dual-model OFDM (DM-OFDM) that employs multiple identifiable signal constellations to enhance spectral efficiency (SE). These approaches have shown greater success but require an increase in receiver complexity to be more effective. In this article, neural network (NN) will be used to address these fundamental difficulties.

In orthogonal frequency-division multiple access (OFDMA), each user is assigned a unique orthogonal subcarrier. On the other hand, MC-CDMA integrates multicarrier modulation (MCM) and code division multiple access (CDMA) to foster variation. This is achieved by spreading data symbols for multiple users across the same set of subcarriers [12]. This is in contrast to OFDMA, which uses a single set of subcarriers.

Zero-forcing (ZF), equal gain combining (EGC), and maximum-ratio combining (MRC) are a few examples of linear detection methods used in practical implementations of MC-CDMA. The combination of MC-CDMA and index modulation (IM) has led to the development of a recent method called IM-MC-CDMA [13–15]. This method transmits data bits utilizing the indices of spreading codes. However, these orthogonal systems cannot provide extensive connectivity in future wireless networks due to limited orthogonal resources. As the number of system users increases, the detection method becomes more sophisticated.

Since the release of the first MC-CDMA receivers into the market, more than a decade has passed. The maximum ratio combining (MRC) receiver, a subclass of the linear receiver family, is unable to eliminate phase distortions caused by channel interference [16]. Although phase distortion caused by channel interference can be remedied, faded signal magnitudes cannot be recovered with equal gain combining (EGC) [17]. Moreover, nonlinear system distortions can occur in some communication systems due to factors such as power amplifiers and faded radio settings.

A considerable residual error is produced even when the MMSE receiver recognizes the broadcast signal by computing noise variance and channel covariance. While a thorough search is key to achieving optimal performance with the ML detector, its use in real-world systems is not recommended due to the complexity and nonlinearity it introduces. Numerous studies have explored the trade-offs between complexity and performance [18, 19].

Most classical detectors assume that the receiver possesses reliable information about the channel state. However, in real-world systems, the channel state information needs to be estimated, which increases the level of complexity. Nonlinear system distortion can be considered an effective decision boundary for signal detection in MC-CDMA, as the optimal decision boundary for this problem is highly nonlinear. In this context, artificial neural network (ANN) models, known for their capability in handling highly nonlinear pattern categorization, can be considered an advantageous option for signal detection [20, 21].

Artificial neural networks (ANNs) are examples of parallel and distributed architectures, where a large number of interconnected units (neurons) process and learn from inputs and encountered patterns simultaneously. Desirable properties of ANNs, such as robustness, finite memory, and the ability to perform nonlinear classification, are relevant to the challenge of signal detection. Consequently, ANNs have gained popularity in recent years as multiuser detectors in space division multiple access-orthogonal frequency division multiplexing (SDMA-OFDM) systems. These systems have demonstrated superior performance compared to standard linear approaches [22–24].

Among different types of ANNs, the multilayer perceptron (MLP) is recognized as a straightforward and highly effective pattern categorization technique [25–28]. Using the MLP, input patterns can be classified into nonlinear decision boundaries. Taking advantage of this, Necmi Taspnar utilized the MLP model as an authoritative signal discovery tool in MC-CDMA systems [29–32].

In this study, the nonlinear falsification that occurs in MC-CDMA networks is not taken into consideration, which means that the DNN receiver does not make use of its full potential. The objective of this work is to identify MC-CDMA system broadcasts in a nonlinearly distorted environment, aiming to fully utilize the capabilities of the DNN receiver and make the most of its potential.

The rest of the document is structured as follows: Section 2 of this article discusses the mathematical description of the received signal and the generalized MC-CDMA system model. Section 3 covers conventional MC-CDMA receivers, including EGC, ORC, and MMSE. For nonlinear MC-CDMA systems, the details of the DNN receiver are provided in Section 4. The outcomes of the simulation study are discussed in Section 5. Finally, the summary and conclusions of the report can be found in Section 6.

2. Model for the MC-CDMA System

The transmitter section of the MC-CDMA system is illustrated in Figure 1. The system has the capacity to serve K users simultaneously, and a spreading code with N bits of length is used to broadcast the data symbol for each user. To perform an inverse fast Fourier transform (IFFT), the data from k users is multiplied by a spreading algorithm. The output of the IFFT is then converted from serial to parallel form and mixed with the data stream from the remaining K–1 users to obtain the final result. The channels receive this signal and transmit it, but it undergoes nonlinear

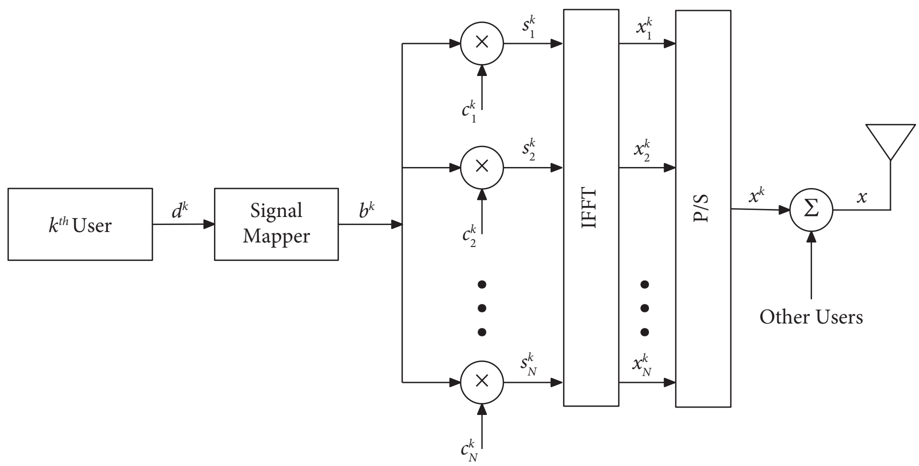


Figure 1: System blocks for MC-CDMA transmitter.

falsification and is affected by channel noise at the receiver [33, 34]. To correct for the distortion of the serial data, a fast Fourier transform (FFT) is performed on the parallelized serial information. The input signal is then received by a signal detector, which uses the FFT to convert the distorted serial information back into parallel form. Afterwards, a signal detector receives the input signal. It is possible to write the transmitted signal vector's discrete baseband form as follows:

$$x_m = \sum_{k=1}^{K}\sum_{n=1}^{N} s_n^k \exp\left(\frac{j2\pi nm}{N}\right), \quad m = 1, 2, ..., N, \tag{1}$$

$$s_n^k = \sqrt{E_c} b^k c_n^k, \quad n = 1, 2, ..., N,$$

where s_n^k is the signal weights, c_n^k is the nth chip of the k-th users spreading sequence, b^k is the data symbols, and $\sqrt{E_c}$ is the energy per subcarrier.

The received signal vector $x = [x_1, x_2, \ldots, x_N]^T$ corresponding to transmitted vector is used to get the discrete base band signal vector x; to put it another way,

$$\mathbf{y} = \mathrm{NL}\,(\mathbf{h} \otimes \mathbf{x}) + \mathbf{w}, \tag{2}$$

where NL is the nonlinearity, H is the impulse response, and w is the AWGN noise.

In this case, N_0 consists of an additive white Gaussian noise (AWGN) with zero mean and power spectral density of N_0 on one side and a nonlinear function NL (.), $\mathbf{h}$ indicates response of the channel [35, 36]. As a result, the n^{th} subreceived carrier's symbol r_n can be represented as follows:

$$r_n = \sum_{m=1}^{N} y_m \exp\left(\frac{-j2\pi nm}{N}\right), \quad n = 1, 2, ..., N. \tag{3}$$

3. Classification Detectors for MC-CDMA

Data symbols from each user are individually identified at the receiver using unique device-based spreading codes, as illustrated in Figure 2. The k-th device's data symbol is estimated for single-user detection as follows:

$$\widehat{b}^k = \sum_{n=1}^{N} g_n c_n^k r_n, \quad k = 1, 2, ..., K, \tag{4}$$

where g_n is a frequency domain equalization gain factor. Nonlinear detectors such as maximum likelihood (ML) for MC-CDMA have been explored in this area, along with classic detectors such as orthogonality restoring combining (ORC) and equal gain combining (EGC) [37]. Receiver gains can be utilized to identify signals and differentiate between each user's information by employing their unique spreading code [38].

3.1. Equal Gain Combining (EGC). Equal gain combining (EGC) is a receiver diversity technique commonly used in multicarrier code division multiple access (MC-CDMA) systems. MC-CDMA is a spread spectrum technique that combines the advantages of both code division multiple access (CDMA) and orthogonal frequency division multiplexing (OFDM). EGC is employed at the receiver to improve the reliability of the received signal by combining multiple copies of the transmitted signal.

In MC-CDMA, the transmitted signal is spread across multiple subcarriers, and each subcarrier is modulated with a different code. This allows multiple users to share the same frequency band simultaneously. However, due to various factors such as multipath fading, interference, and noise, the received signal at the receiver may be degraded. EGC operates by utilizing multiple receive antennas or multiple receive paths to capture multiple copies of the transmitted signal. Each copy may experience different channel conditions due to the presence of multipath or interference. The objective of EGC is to combine these copies in a way that maximizes the signal quality and reduces the effects of fading and interference.

The combining process in EGC involves adding up the received copies of the signal after they are suitably weighted. The weights applied to each copy depend on the channel conditions associated with that particular copy. The combining weights are typically determined based on the received signal strength or the channel quality indicators. In

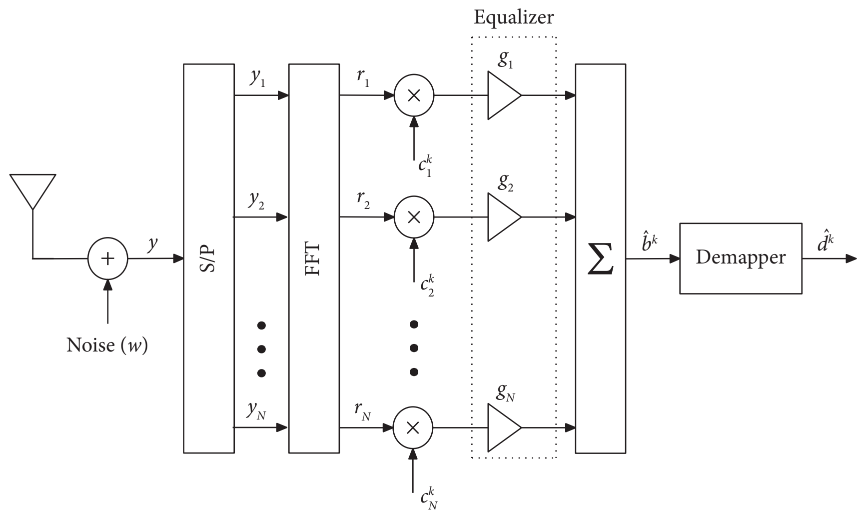


FIGURE 2: System blocks for MC-CDMA receiver.

EGC, the combining weights are set to be equal, regardless of the channel conditions of each receive path. This means that each copy of the received signal is given equal importance in the combining process. The combined signal is then passed through a demodulator to extract the original transmitted data. By combining multiple copies of the transmitted signal, EGC mitigates the detrimental effects of fading and interference. It helps improve the overall signal quality, increase the system capacity, and enhance the reliability of the communication link in MC-CDMA systems.

Until there is a high degree of orthogonality in the spreading codes of distinct users, the MC-CDMA receiver performs admirably. However, multipath propagation in the medium may destroy the orthogonality of spreading codes [39]. A code's orthogonality may be further harmed by the MRC scheme's optimal combination of multipath components. By using equal gain combining (EGC), a detector that corrects phase distortion, you can prevent this issue. Thus, the EGC detector g_n's equalization gain is

$$g_n = \frac{H_n^*}{|H_n|}. \tag{5}$$

3.2. Maximal Ratio Combining. A powerful signal is assigned greater weight by the diversity combiner in the maximal ratio combining (MRC) scheme, as it enables more reliable communication. Maximal ratio combining is another receiver diversity technique commonly used in multicarrier code division multiple access (MC-CDMA) systems. Similar to equal gain combining (EGC), MRC is employed at the receiver to enhance the reliability and performance of the received signal by combining multiple copies of the transmitted signal.

In MC-CDMA, the transmitted signal is spread across multiple subcarriers, and each subcarrier is modulated with a different code. MRC utilizes multiple receive antennas or receive paths to capture multiple copies of the transmitted signal, each experiencing different channel conditions due to multipath or interference. The main difference between MRC and EGC lies in the combining weights used in the combining process. In MRC, the combining weights are determined based on the channel conditions associated with each receive path. The combining weights are set to be proportional to the inverse of the received signal power or signal-to-noise ratio (SNR) of each path.

The combining process in MRC involves multiplying each received copy of the signal by its corresponding combining weight and then adding up the weighted copies. The objective is to give more weight to the copies with better channel conditions (higher SNR) and less weight to the copies with poorer channel conditions (lower SNR). By assigning higher weights to the better quality copies, MRC optimally combines the received signals and maximizes the signal-to-noise ratio at the output. This results in improved performance and increased reliability in the presence of fading and interference. After the combining process, the combined signal is passed through a demodulator to extract the original transmitted data. MRC effectively mitigates the adverse effects of fading, interference, and noise, leading to enhanced system capacity and improved overall performance in MC-CDMA systems.

Equalization gain (g_n) is calculated as follows:

$$g_n = H_n^*. \tag{6}$$

Multiple user interference is possible due to the multipath propagation destroying the orthogonality of the various spreading codes used by different users. It is possible that the MRC and EGC detectors will fall short in eliminating multiuser interference (MUI). In contrast, ORC or zero forcing (ZF) equalizer retains the orthogonality of the individual users by cancelling the channel transfer function (CTF). The approximation and reversal effects of the CTF can be used to negate this signal [40].

In other words, the ORC detector g_n's equalization gain is provided by

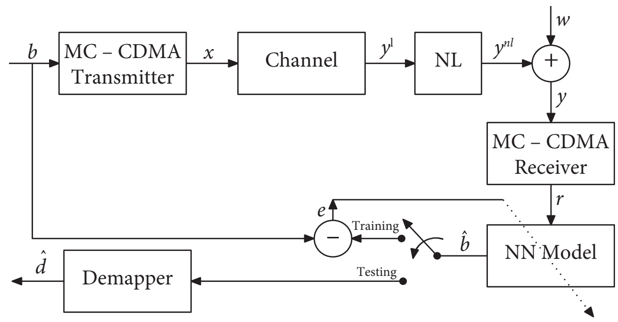


Figure 3: MC-CDMA receiver based on NN.

$$g_n = \frac{H_n^*}{\left|H_n\right|^2}. \tag{7}$$

4. Proposed NN Receiver Based on Deep Neural Network (DNN)

Figure 3 displays the receiver configuration of an MC-CDMA system using neural network (NN). The MC-CDMA framework is initially followed, and then training symbols are utilized to build the NN receiver model. An adaptive method needs to be recursively executed during network training to adjust the network's free parameters based on errors. Neural networks can be trained by modifying the weights between individual pairs of neurons until the desired output is achieved. In the NN model shown in Figure 3, a $(N \times 1)$-dimensional recognized received classification "r" is provided as input, which corresponds to a $(K \times 1)$-dimensional communicating signal vector "b." The error is calculated by comparing the $(K \times 1)$-dimensional response vector of the neural system to the corresponding response "b." After training, the NN model is tested and used as a signal detector. The response provides an estimate of the quality of the sender's signal.

For nonlinear signal classification, the feed-forward DNN model has been found to be the most successful. In the brain's three phases of neurons, there exists an input phase, supplementary hidden phases, and one or more output layers. The activation functions of the hidden and output phases can be chosen as nonlinear, taking into account the characteristics of the channel. By using the classic backpropagation (BP) method, the change in network weights is calculated twice, allowing for the training of a DNN network. An output is generated by propagating an input vector through a network with fixed weights. The difference between the actual output and the desired output is used to determine the output error. This error is then propagated backward through the network during the reverse pass, and the weights are adjusted accordingly.

Figure4shows the structure of the DNN model that is used for the MC-CDMA receiver. Input consists of N layers, hidden input consists of H_{N} neurons, and output consists of K neurons. In this context, N refers to the whole length of the chip, and K indicates the total number of people who will use it. Neurons in these levels are linked together in a process known as "feed forward." Individual neuron in hidden phase takes a summer and an activation rule that is not linear, as shown in Figure 5.

The output layer consists of a straightforward operator for performing arithmetic operations.

It is possible to update the weights of DNN network connections in a time-efficient manner by utilizing the backpropagation (BP) technique, which is an iterative process.

Using a deep neural network (DNN) in the context of MC-CDMA involves harnessing the power of machine learning to enhance various aspects of the system, including channel estimation, interference mitigation, and signal detection. While I can provide a high-level overview, it is important to note that the mathematical derivation of a specific DNN architecture for MC-CDMA would require a detailed understanding of the specific design choices, network architecture, and training methodology. Here is a general outline of how a DNN can be applied to MC-CDMA:

(i) *Data Representation*. The input to the DNN consists of the received signal samples or features derived from them. These samples are usually represented as complex-valued vectors, where each element corresponds to a different subcarrier.

(ii) *Network Architecture*. The specific architecture of the DNN can vary depending on the application. For MC-CDMA, a common choice is a feedforward neural network with multiple hidden layers. Each layer consists of a set of neurons that perform nonlinear operations on their inputs.

(iii) *Training Data*. A DNN requires a large amount of labeled training data to learn the mapping between the input (received signal samples) and the desired output (e.g., channel estimates or detected symbols). This training data can be generated by simulating various channel conditions and the corresponding transmitted symbols.

(iv) *Loss Function*. A loss function is defined to quantify the discrepancy between the DNN's predicted output and the ground truth labels in the training data. The choice of the loss function depends on the specific task being addressed, such as mean squared

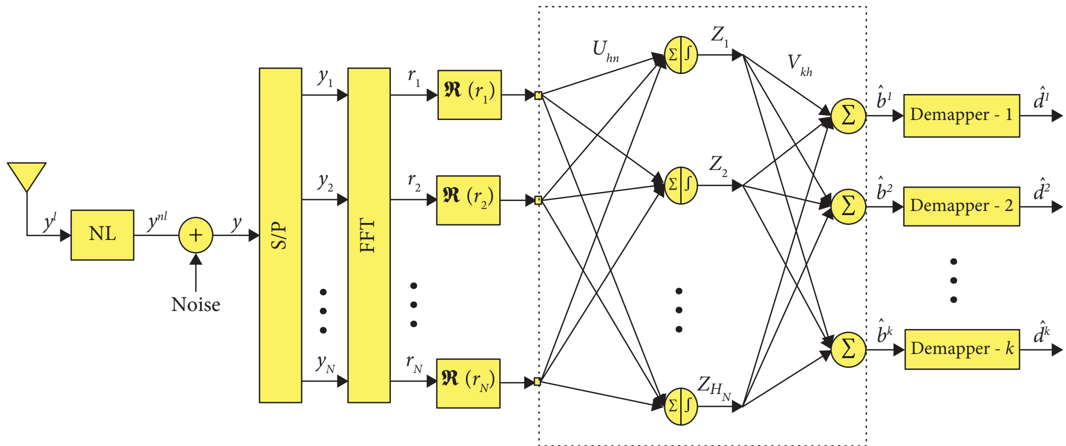


Figure 4: MC-CDMA receiver based on DNN NN.

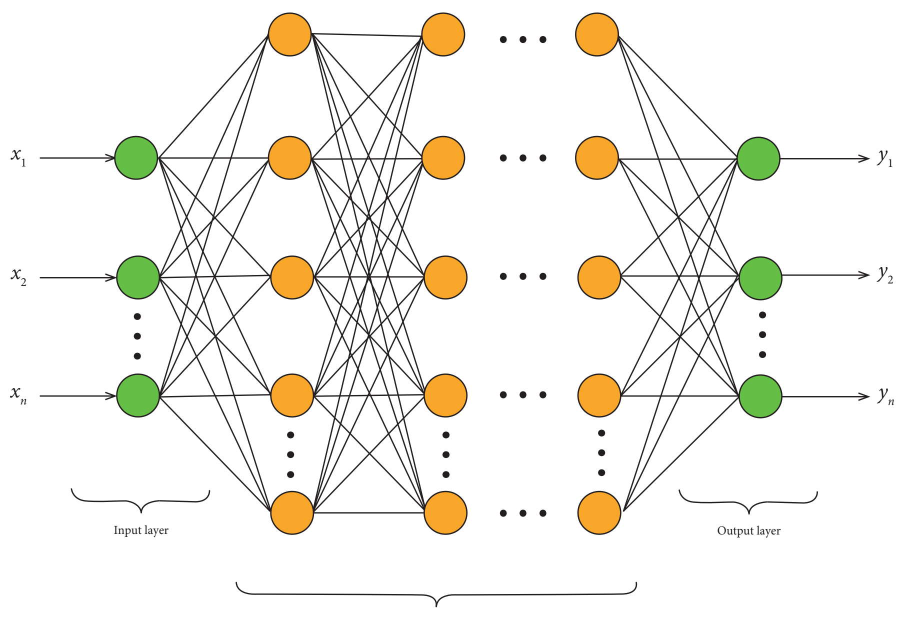


Figure 5: Typical structure of DNN NN.

error (MSE) for channel estimation or cross-entropy loss for symbol detection.

(v) *Backpropagation and Gradient Descent*. The DNN is trained using an optimization algorithm called backpropagation combined with gradient descent. In this process, the gradient of the loss function with respect to the network parameters is computed, and the weights of the network are updated in the opposite direction of the gradient to minimize the loss.

(vi) *Forward Pass and Inference*. Once the DNN is trained, it can be used for inference on unseen data. Given the received signal samples as input, the DNN performs a forward pass, propagating the input through the network to produce the desired output, such as channel estimates or detected symbols.

It is important to note that the specific mathematical derivation of a DNN for MC-CDMA depends on the network architecture chosen, the training methodology employed, and the specific goals of the application. Detailed derivations would involve defining the activation functions, specifying the number of layers and neurons, and formulating the loss function and the associated optimization algorithm. These details would need to be addressed based on the specific design choices made for the DNN in MC-CDMA.

To provide a mathematical representation of a deep neural network (DNN) in the context of MC-CDMA, let us consider a simple feedforward neural network architecture with one hidden layer. This architecture can be used for tasks such as channel estimation or symbol detection. Here are the mathematical equations involved:

(i) Input representation:

(1) Let $x = [x_1, x_2, \ldots, x_n]$ be the received signal samples or features, where n is the number of subcarriers.

(2) Each x_k represents the received signal sample on the k-th subcarrier.

(ii) Hidden layer:

(1) Let $h = [h_1, h_2, \ldots, h_m]$ be the output of the hidden layer, where m is the number of neurons in the hidden layer.

(2) Each h_j represents the output of the j-th neuron in the hidden layer.

(3) The output of the hidden layer can be computed using an activation function such as the sigmoid or rectified linear unit (ReLU): $h_j = f(\sum(w_{jk} * x_k) + b_j)$, where w_{jk} is the weight connecting the k-th input to the j-th neuron, b_j is the bias of the j-th neuron, and $f(\cdot)$ is the activation function.

(iii) Output layer:

(1) Let $y = [y_1, y_2, \ldots, y_p]$ be the output of the neural network, where p is the number of outputs (e.g., channel estimates or detected symbols).

(2) The output layer can be computed similarly to the hidden layer, with its own set of weights and biases: $y_i = g(\sum(v_{ij} * h_j) + c_i)$, where v_{ij} is the weight connecting the j-th neuron in the hidden layer to the i-th output, c_i is the bias of the i-th output, and $g(\cdot)$ is the activation function (which can vary depending on the task).

(iv) Loss function:

(1) A loss function is used to measure the discrepancy between the network's predicted output y and the ground truth labels.

(2) The choice of the loss function depends on the specific task, such as mean squared error (MSE) for channel estimation or cross-entropy loss for symbol detection.

(v) Training:

(1) The DNN is trained by adjusting the weights and biases to minimize the loss function using an optimization algorithm such as stochastic gradient descent (SGD) or Adam.

(2) This is done through backpropagation, which involves computing the gradients of the loss function with respect to the network parameters and updating the weights and biases accordingly.

Once the DNN is trained, it can be used for inference on unseen data. Given the received signal samples x as input, the network performs a forward pass, computing the hidden layer outputs h and the final outputs y. The specific mathematical equations will depend on the architecture, activation functions, and training methodology chosen for the DNN in MC-CDMA.

5. Simulation Results

Figure 6 displays MC-CDMA systems with either linear or nonlinear system distortion, along with the mean bit error rate (BER) of sixteen different devices. This average BER estimation considers the EGC, MRC, ZF, MMSE, MLP, and DNN receivers. When nonlinear distortion is introduced to the MC-CDMA system, linear detectors such as MMSE, EGC, and MRC are unable to effectively reduce the distortions in the received signals, resulting in residual interference. This is because linear detectors operate on a linear basis, which explains their limitations in handling nonlinear distortions. The presence of nonlinearities significantly impacts the performance of classical receivers, as measured by their BER. In contrast, MLP neural networks have greater nonlinear classification capacity, enabling them to perform closer to the ideal ML receiver. It is worth noting that the MLP receiver achieves a signal-to-noise ratio (SNR) of 18 decibels (dB), while the MMSE receiver requires an SNR of 24 decibels (dB) to achieve an effective error rate (BER) of 10–4. This highlights the improved performance of the MLP receiver compared to the MMSE receiver.

Figure 7 displays the signal constellation estimates of several receivers, demonstrating the effect of nonlinear distortion. The predicted signal constellation of User-1 is shown in Figure 7, and this continues to Figure 8, with User-1 continuously transmitting "−1" in a comprehensive data frame at 12 dB. Classical receivers like MRC and EGC are unable to automatically correct output symbol amplitude and phase distortions. In contrast, MMSE assumes knowledge of the channel covariance and noise variance. As a result, its predicted symbols are located closer to the decision boundary of binary phase shift keying, with few of them even crossing it and entering the wrong half-plane.

Dynamic MLP receivers utilize phase improvement algorithms during network training to compensate for random amplitude and phase distortions in output symbols, addressing the distortions that can occur. Consequently, the predicted symbols cluster around the actual transmitted signal in close proximity. Figure 9 illustrates the performance evaluation of the MC-CDMA system when communicating with varying numbers of users, providing an assessment of the robustness of the MLP receiver.

Figure 9 depicts the bit error rate (BER) of User-1 in a nonlinear MC-CDMA at a dB level of 12 for various user counts. As more users employ multiple access strategies such as MC-CDMA systems, the multiple access interference (MAI) increases. The decrease in BER performance observed in Figure 8 across all MC-CDMA receivers can be attributed to the growing number of users.

The MLP receiver incorporates varying numbers of hidden nodes, allowing it to construct the necessary decision boundaries for signal classification as the number of user changes. However, the graph illustrates that the MLP's performance significantly declines compared to the other traditional receivers. While the MLP receiver achieves a BER

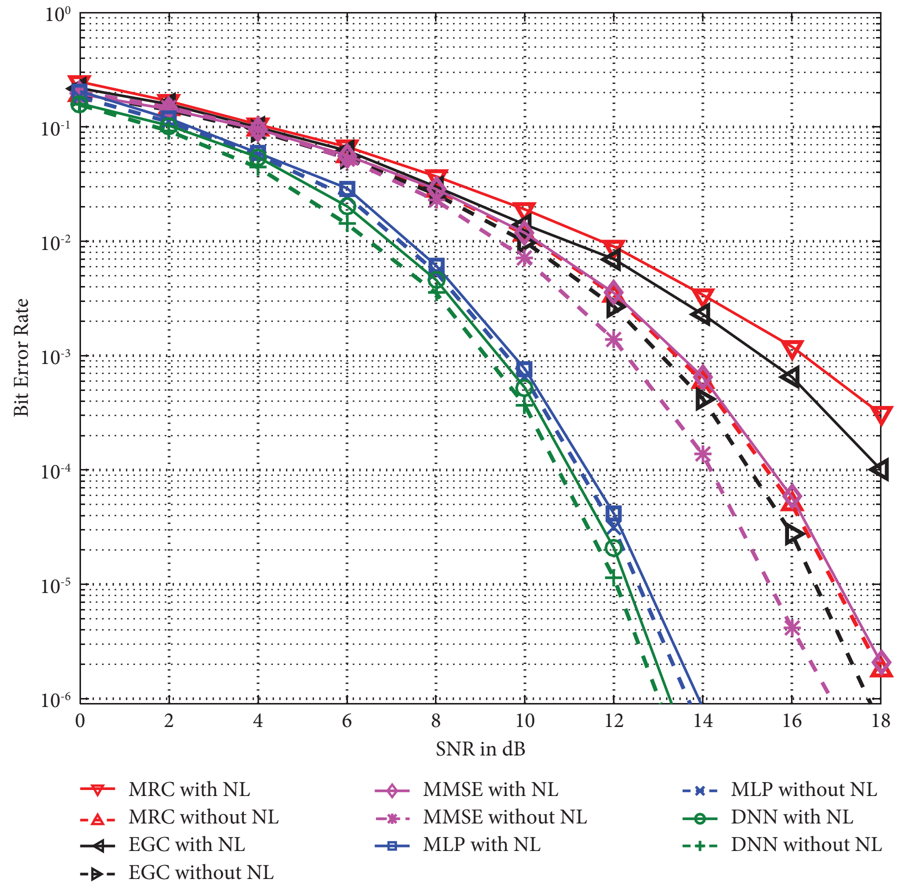
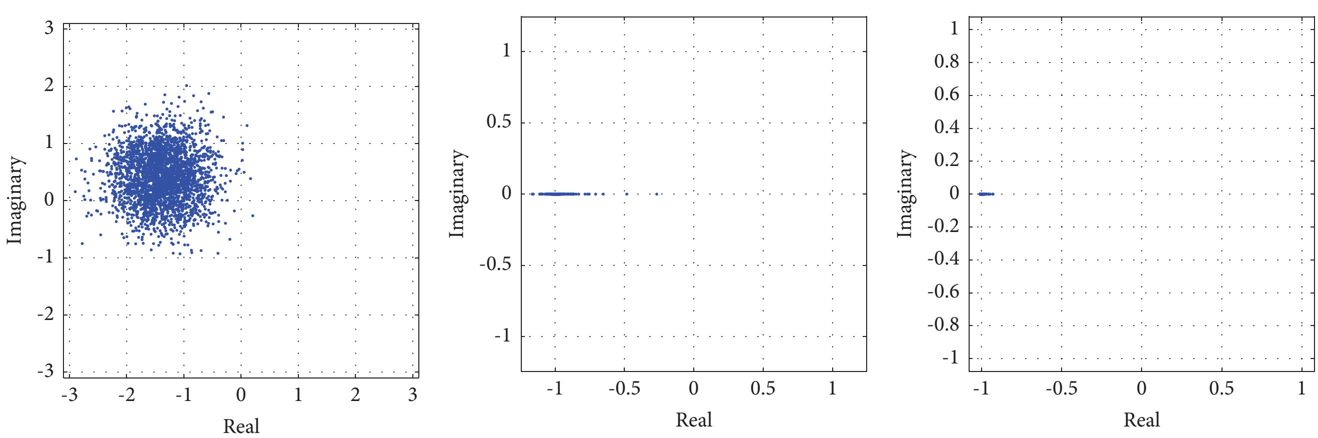


Figure 6: Average BER of various detectors in the nonlinear and linear MC-CDMA system.



(a) (b) (c)

Figure 7: Constellation diagrams of detected symbols of User-1 in the absence of nonlinearity at 10 dB SNR using (a) MMSE, (b) MLP, and (c) DNN.

of 10^{-4} when the system communicates with ten users, the EGC, MRC, and MMSE estimators display BERs of 0.04, 0.1, and 0.01, respectively.

Although the ML receiver exhibits the best performance among the MC-CDMA system's receivers, its computational complexity is extremely high. The processing power required for the ML receiver grows exponentially by 2 mK for each additional user and modulation order. To compare the computational complexity of the ML detector with that of the MLP receiver and the classical receivers proposed by this research, Table 1 provides a contrast.

The complexity of neural networks (NNs) is influenced by various factors such as the number of training samples (NT) and data symbols in individual information frames,

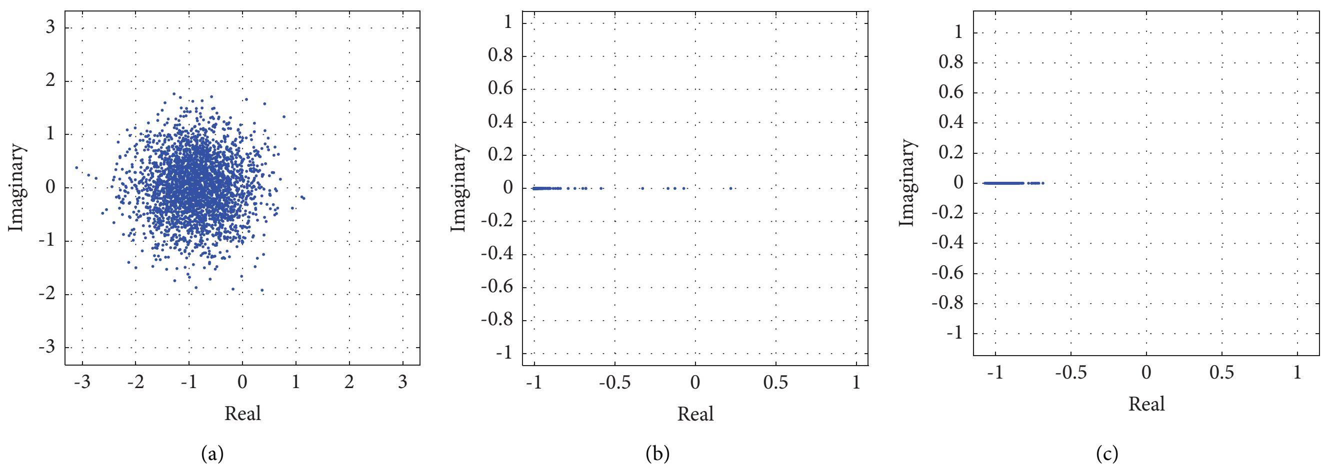


FIGURE 8: Constellation diagrams of detected symbols of User-1 in the presence of nonlinearity at 10 dB SNR using (a) MMSE, (b) MLP, and (c) DNN.

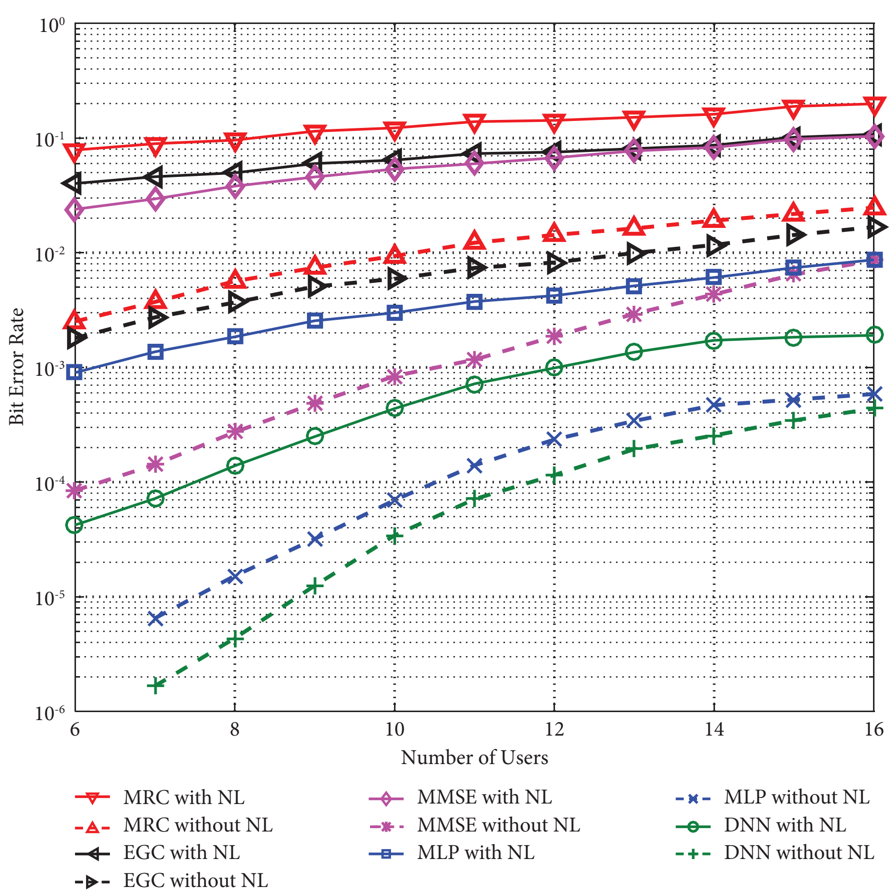


FIGURE 9: User-1's BER while varying number of users using different receivers at 10 dB Eb/No.

which play a crucial role in achieving the lowest mean square error (MSE). As a result, the complexity of the MLP scales linearly with NT and M. Refer to Table 2 for the selected parameters for this investigation.

Table 3 represents the required signal-to-noise ratio (SNR) values in decibels (dB) for different receiver techniques in a particular scenario. Here is an explanation of each receiver technique and the corresponding SNR values:

(1) *DNN (Deep Neural Network)*. In Figure 6, the DNN-based receiver technique requires an SNR of 11 dB to

Table 1: A comparison of complexity of various receivers.

Recipient	Action	Complication	Overall complexity	Percentage of maximum likelihood
EGC	Summing up	$(N^2 + M + K) \times (N - 1)$	48.87×10^3	1.062
	Multiplication	$(K + M + N) \times N^2$	77.4×10^4	1.184
MRC	Summing up	$(N - 1) \times (\mathrm{K} + \mathrm{M})$	45×10^3	0.98
	Multiplication	$N^2 \times (K + M)$	77×10^3	1.125
MLP	Summing up	$[H_N \times N_T \times (3K + 2N + H_N - 1)] + [\mathrm{M} \times \{\mathrm{H_N} \times (\mathrm{K} + \mathrm{N} - 1) - \mathrm{K}\}]$	59.19×10^4	1.285
	Multiplication	$[H_N \times M \times (K + N)] + [H_N \times N_T \times (5K + 2H_N + 4N)]$	98×10^4	1.49
DNN	Summing up	$[H_N \times (2K + 5N + 3H_N + 1)] + [M \times \{H_N \times (K + 2N - 1)\}]$	8.14×10^4	0.18
	Multiplication	$[H_N \times 2M \times (K + N)] + [H_N \times (3K + 2H_N + 4)]$	12.21×10^4	0.19
ML	Summing up	$2^{mK} \times M \times [N \times K \times (N + K - 1) - 1]$	46.029×10^6	100
	Multiplication	$M \times N \times 2^{mK} \times (N \times K + K^2 + K + 1)$	65.3×10^6	100

TABLE 2: Model attributes.

Parameter	Description
Length of the chip (N)	64
Modulation type	BPSK
Frame data (N_F)	3000
Subcarriers	64
Spreading code type	Walsh
Data symbols per frame (M)	9000
Users (K)	16
Deployed medium	SUI, Rayleigh
Number of training symbols (N_T)	2500
Nonlinearity	$b(k) = a(k)–0.1\mathrm{a}^3(\mathrm{k}) + 0.2\mathrm{a}^2(\mathrm{k})$ [25]
The number of test symbols	9000
Learning rate parameter (μ)	0.85
MLP training algorithm	Backpropagation

TABLE 3: The SNR values required to achieve BER of 10^{-4} for various receivers.

Figure no.	Receiver	SNR required in dB
Figure 6	DNN	11
Figure 6	MLP	11.5
Figure 6	MMSE	15.5
Figure 6	EGC	18
Figure 6	MRC	21

achieve satisfactory performance. This suggests that the DNN is designed to handle a certain level of noise and interference while still being able to accurately detect and recover the transmitted signal.

(2) *MLP (Multilayer Perceptron)*. MLP is a type of neural network architecture. In Figure 6, the MLP-based receiver technique requires a slightly higher SNR of 11.5 dB compared to the DNN. This indicates that the MLP architecture, which typically consists of fully connected layers, may have slightly lower noise tolerance or may require additional SNR to achieve similar performance as the DNN.

(3) *MMSE (Minimum Mean Square Error)*. MMSE is a classic linear receiver technique that aims to minimize the mean square error between the received and estimated signals. In Figure 6, the MMSE-based receiver technique requires a higher SNR of 15.5 dB. This suggests that the MMSE receiver requires a stronger received signal compared to the neural network-based approaches to achieve the desired performance level.

(4) *EGC (Equal Gain Combining)*. EGC is a receiver diversity technique that combines multiple copies of the received signal with equal weights. In Figure 6, the EGC-based receiver technique requires an SNR of 18 dB. This indicates that EGC, which combines multiple receive paths with equal weights, requires a higher SNR compared to the neural network and MMSE techniques.

(5) *MRC (Maximal Ratio Combining)*. MRC is another receiver diversity technique that combines multiple copies of the received signal with weights proportional to the received signal power. In Figure 6, the MRC-based receiver technique requires the highest SNR of 21 dB among the mentioned techniques. This implies that MRC, which gives more weight to stronger received signals, requires the strongest received signal among the receiver techniques considered.

It is important to note that these SNR values are specific to the scenario or simulation mentioned in Figure 6 and may vary depending on the system parameters, channel conditions, and performance requirements.

6. Conclusion

We propose an innovative DNN receiver for the MC-CDMA system that can optimize both linear and nonlinear distortions in a fully data-driven manner. The obtained results indicate the required signal-to-noise ratio (SNR) values in dB for different receiver techniques, namely, DNN, MLP, MMSE, EGC, and MRC. These values reflect the signal quality needed for each receiver technique to achieve satisfactory performance in a given scenario. Based on the figures, it can be observed that the DNN-based receiver requires the lowest SNR of 11 dB, followed closely by the MLP-based receiver at 11.5 dB. This suggests that the neural network-based approaches, specifically DNN, have relatively better noise tolerance and can operate effectively even at lower SNR levels. The MMSE-based receiver requires a higher SNR of 15.5 dB compared to the neural network-based techniques. MMSE is a linear receiver that may be more sensitive to noise and interference, requiring a stronger received signal for accurate signal detection and recovery. The EGC-based receiver technique requires an even higher SNR of 18 dB, indicating that the EGC diversity technique, which combines multiple receive paths with equal weights, demands a relatively stronger received signal to effectively mitigate the effects of fading and interference. Lastly, the MRC-based receiver requires the highest SNR of 21 dB among the mentioned techniques. MRC is a diversity technique that gives more weight to stronger received signals; consequently, requiring the strongest received signal among the considered receiver techniques. Further research and development could focus on the following aspects:

(1) *Optimization of Neural Network Architectures*. Exploring more sophisticated DNN or MLP architectures and optimizing hyperparameters, employing advanced training techniques, can potentially improve the performance of neural network-based receivers at lower SNR levels.

(2) *Adaptive Receiver Techniques*. Investigating adaptive techniques that dynamically adjust receiver parameters, such as combining weights or equalizers, based on the channel conditions and SNR can enhance the efficiency and adaptability of the receivers.

(3) *Hybrid Receiver Designs*. Exploring hybrid receiver designs that combine the strengths of different receiver techniques, such as combining neural network-based processing with traditional linear receivers or diversity techniques, can potentially achieve better performance in various SNR regimes.

(4) *Resource Allocation Strategies*. Developing efficient resource allocation strategies that allocate subcarriers and power optimally based on the channel conditions and SNR can enhance the overall system performance and maximize the utilization of available resources.

Abbreviations

MC-CDMA:	Multicarrier code division multiple access
MMSE:	Minimal mean squared error
OFDMA:	Orthogonal frequency-division multiple access
MRC:	Maximum ratio combining
EGC:	Equal gain combination
ANN:	Artificial neural network
SDMA-OFDM:	Space division multiple access-orthogonal frequency division multiplexing
IFFT:	Inverse fast Fourier transform
FFT:	Fast Fourier transform.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Ravikumar C.V. conceptualized the study, developed the methodology, provided the software, wrote the article, and supervised and investigated the study. Kalapraveen Bagadi curated the data and performed formal analysis. Asadi Srinivasulu contributed to proof reading and performed plagiarism check. Rushendrababu K. reviewed and edited the article. Sathish K. provided the software and wrote the article.

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