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An Optimized Deep Neural Network with Heuristic Algorithm for PAPR Reduction Model in OFDM Communication Systems

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Abstract

Orthogonal Frequency Division Multiplexing (OFDM) is a flexible method utilized in several wireless and wired standards because of its poor complexity receiver model and robustness in multipath propagation environments. The OFDM communication model attains superior data rates and spectral efficiency for mobile wireless communication systems. Although this scheme provides superior Quality of Service (QoS), it attains a high Peak-to-Average Power Ratio (PAPR), which is considered as a complicated problem and also needs to be determined in the OFDM scheme. The PAPR creates distortion in the transmitted signal because of the power amplifier's nonlinearity. As a result, the PAPR minimization of the OFDM model is one of the significant experimental topics in OFDM and has been the topic of detailed examination by numerous experts. Though there have been various PAPR reduction techniques in the past years, the models can't decrease the system's Bit Error Rate (BER) because of the signal distortion. Therefore, a new strategy is required for the PAPR reduction in the OFDM system. In this paper, a new PAPR reduction strategy is implemented with the help of Optimized Deep Neural Networks (ODNN), where the parameters of DNN like hidden neuron count and epochs are optimized through a new Improved Billiards-inspired Optimization Algorithm (I-BOA). This suggested framework is employed to determine the constellation demapping and mapping in each subcarrier. The major goal of the developed framework is to reduce the PAPR and BER in the communication system. Different validations are executed in the developed framework to display the efficiency of the PAPR and BER. While considering PAPR, the findings of the developed I-BOA-ODNN method achieve 17.7%, 19.4%, 16.5%, and 14.6% than Genetic Algorithm (GA), Particle Swarm Algorithm (PSO), Artificial Bee Colony Algorithm (ABC), and Billiards-inspired Optimization Algorithm (BOA) in terms of the mean. Throughout the validation, the offered I-BOA-ODNN model performs superior to the existing heuristic algorithms.

Keywords: Orthogonal Frequency Division Multiplexing; Peak-to-Average Power Ratio Reduction; Optimized Deep Neural Networks; Improved Billiards-Inspired Optimization Algorithm.

How to Cite This Article

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Introduction

Importance of the Study

Wireless technology is the major approach in the communication field, which offers superior data transmission for 4G and 5G communications. In the wireless communication system, the demand for higher-speed data transmission is increased [1]. The OFDM theory states that it is a way of multi-carrier modulation. It is a category of signal modulation that offers a higher data rate modulated with a stream of sub-carriers that must be orthogonal to each other [2]. The major benefit of using the OFDM scheme is to provide higher bandwidth efficiency, spectral efficiency, and increased system efficiency for reliable transmission. OFDM signals have been widely utilized in most wireless communication systems [3]. However, these signals face complications in terms of high PAPR that cause out-of-band radiation and in-band distortion. On the other hand, several PAPR minimization approaches have been suggested in OFDM systems including Partial Transmit Sequence (PTS), Selective Mapping (SLM), coding, and clipping. To reduce the PAPR, SLM and PTS have been utilized in various studies. These two approaches are considered as probabilistic methods as these approaches can minimize the possibility of occurring higher peaks in OFDM signals without any distortion [4]. These SLM and PTS strategies, along with their enhanced versions produce candidate or alternative sequences for presenting similar information with diverse phases. Next, the lower PAPR sequence is chosen by the transmitter for transmission. The superior PAPR reduction efficiency is attained by having more candidate sequences. Conversely, this improvement is accomplished at the cost of enhancing the system's complexity [5].

Among various famous strategies to decrease the PAPR in an OFDM system, the clipping approach is the most suitable one, in which the distortion of the original signal is carried out deliberately [6]. Even though the PAPR of an OFDM system is minimized by the clipping scheme, the degradation in terms of BER is observed by this scheme owing to the signal distortion [7]. Moreover, in the signal-scrambling technique, the phase attribute [8] to produce a scrambled signal is required at the receiver to properly regenerate the transmitted data [9]. The efficiency is significantly minimized when this side information is imprecise. In addition, the huge computational complexity is noticed by the signal scrambling scheme in finding the phase factor that produced an optimal scrambled sequence [10]. Additionally, a nonlinear companding transform scheme is implemented to minimize the PAPR [11], yet it degrades the BER like the clipping scheme [12]. Here, bandwidth efficiency is utilized to measure how efficiently the available bandwidth is utilized to transmit data. Its unit is specified as transmitted data per unit bandwidth (bps). Spectral efficiency measures the amount of available spectrum utilized for transmitting the data. Its unit is defined as the rate of data transmission per unit of the frequency spectrum. System efficiency depends on various factors such as bandwidth usage, power consumption, and error rates. It reflects the overall effectiveness of the system in attaining its communication objectives. By maximizing bandwidth efficiency, spectral efficiency, and system efficiency, communication systems achieve higher data throughput and overall optimized performance, leading to enhanced reliability in transmitting and receiving data.

In most of the existing studies, machine learning, particularly deep learning has achieved extraordinary performance regarding PAPR reduction. The peak-canceling signals are explored by employing an Artificial Neural Network (ANN) [13]. The clustering of signals is done based on the outcomes of the existing tone reservation technique [14]. Likewise, the training time has been reduced with the help of a deep technique-based tone reservation algorithm. A DNN-based Packet Radio Network (PRNet) is suggested for improving the performance of OFDM in the conventional experiment. This experiment used a black box scheme with enciphering and deciphering sections of the OFDM system by utilizing an autoencoder scheme. A real-valued neural network has been proposed in the time domain for the reduction of PAPR and reconstructed the signals simultaneously, intending to minimize the computational complexity [15]. Further, the deep learning tone reservation scheme termed Tone Reservation Network (TRNet) has been introduced with a transmitter network [16]. These abovementioned data-driven techniques accomplish remarkable BER and PAPR performance through the optimization of the black-box neural network. However, most of the conventional neural networks are trained with huge input data [17]. In the meantime, various trainable constraints lead to higher computational complexity [18]. These challenges in the existing studies specify the need to implement a new model for PAPR reduction.

Related Studies

In 2018, Kim *et al.* [19] have implemented a new PAPR reduction strategy named PRNet with the autoencoder architecture. It has determined the demapping of symbols and constellation mapping on every subcarrier. The joint minimization of PAPR and BER was taken as the major objective of the OFDM system.

In 2024, Siddegowda *et al.* [20] have suggested a new PTS approach that helped to reduce PAPR. Here, the signal was transmitted through the noisy channel from transmitter to receiver. The designed framework was suitable for OFDMA uplink systems through frequency division multiplexing. The outcome of the proposed model was assessed based on several performance criteria. Thus, the attained outcome was enhanced than other baseline models.

In 2022, Nguyen *et al.* [21] have designed a novel PTS optimization using phase quantization to lower PAPR. Here, the convex relaxation method was utilized to reduce the time duration needed for the transmission of the signal. The efficiency of the designed framework was estimated with computer simulations. The acquired results have specified that the accessible method has exhibited an enriched performance.

In 2020, Ahmad *et al.* [22] have proposed a unique modulation method to lower the PAPR of an OFDM-based Visible Light Communication (VLC) system by combining Gaussian Minimum Shift Keying (GMSK) pulse shaping with Discrete Fourier Transform (DFT) precoding. The findings demonstrated that various iterations of the suggested scheme outperformed their DFT precoded in terms of PAPR, SER, and power-saving capabilities. The suggested model was also analyzed and implemented to reduce the computational burden, spectral efficiency, and PAPR for the communication system.

In 2019, Wang *et al.* [23] have formulated an approach termed Scaling Signal to Clipping Noise Ratio (S-SCR), where an optimized vector was taken as a scaling factor that has formulated with peak regeneration factors. The outperformance of the designed scheme was verified with existing approaches, where comparable BER performance with superior PAPR reduction efficiency was observed in less number of iterations.

In 2020, Lv *et al.* [24] implemented a GA-based Bilayer Partial Transmit Sequence (GA-BPTS) method for reducing computational complexities, where every subblock was partitioned and transformed into the single-layer framework of the existing PTS scheme. It was fed into a structure of bilayer phase factor search and then introduced a penalty threshold. Further, GA was used for obtaining the vector regarding the suboptimal phase factor. Consequently, the recommended GA-BPTS system has effectively reduced the PAPR before processing and the designed prototype filter provided better effectiveness.

In 2020, Zhang and Shahrrava [25] have implemented a PAPR reduction framework with high performance and lower complexity for OFDM signals. This work used a two-stage cascade framework, where a group of high-order Quadrature Amplitude Modulation (QAM) sequences was constructed from Binary Phase-Shift Keying (BPSK) and Quadrature-PSK (QPSK) sequences. In the second stage, the optimal Class-III SLM scheme was utilized with a collection of parallel blocks. It has further generated several candidate sequences by forwarding them via a group of parallel sub-blocks, which has performed circular shifting with optimum shift values and circular convolution with perfect sequences. The practical outcomes of the accessible method have shown higher efficiency of the developed model than conventional schemes regarding lower complexity and PAPR reduction.

In 2021, Wang *et al.* [26] have studied a deep learning technique model-driven technique in OFDM systems for reducing the PAPR. Particularly, a deeply structured architecture was taken as an iterative peak-canceling signal generation framework, where the designed model has been included in the tone reservation approach. While evaluating the traditional schemes, the experimental study has shown the competence of the designed framework in terms of lower training costs and complexity with reasonable PAPR performance.

In 2024, Elaage *et al.* [27] have discussed several strategies including SLM, clipping, and PTS. Further, this work concentrated on increasing the tone reservation's performance concerning PAPR minimization and convergence speed. This work utilized distinct algorithms on the basis of the gradient technique. It has been revealed that the model improved the convergence speed and minimized the PAPR.

In 2023, Timande and Nigam [28] have portrayed the OFDM system's PAPR minimization by employing the SLM and filtering mechanisms. The simulated solutions displayed that the model was relatively suitable for reducing the PAPR efficiency without compromising the BER and the system's simplicity.

In 2024, Qasem *et al.* [29] have presented a pilot-assisted mechanism. It resolved the deterioration of the spectral efficiency by sending only the candidate index, which minimized the PAPR. This framework validated over conventional models and provided improved performance concerning BER and energy efficiency.

In 2024, Alrakah *et al.* [30] have introduced an analytical experiment of signal clipping that results in distortion in the OFDM systems. Here, a pilot-assisted mechanism was employed to minimize the PAPR of the OFDM system. The developed model minimized the BER. The performance of the process was investigated and further contrasted to that of the existing mechanisms and the solutions displayed the increased performances.

In 2024, Arulkarthick *et al.* [31] have developed a hybrid mechanism, in that the OFDM signal was precoded. After that, the intermediate signal was sine companded to decrease the OFDM signal's PAPR value. It was proved that the developed model relatively minimized the PAPR value. Moreover, the performance of the BER also improved when contrasted with the raw OFDM signal.

In 2024, Sharma *et al.* [32] have designed a PAPR reduction mechanism for OFDMS by utilizing the Osprey Optimization Algorithm (OOA). To minimize the OFDM device's computational expenses, the OFDM was utilized. The suggested work was validated with distinct traditional frameworks and the outcomes revealed the reduced computational expenses.

In 2016, Taspina, and Bozkurt [33] have designed a PAPR minimization strategy for OFDM devices on the basis of the integration of the Backtracking Search Algorithm (BSA) with PTS. The PTS mechanism displayed better PAPR minimization functionality, yet it demanded a complex estimation to explore the optimum attributes. To reduce the search process's complexity the PTS mechanism was combined with BSA. The simulation solutions explained that the computational burden of the system was minimized.

In 2024, Siddegowda and Sampaiah [34] have suggested a Chaotic Sand Cat Swarm Optimization (CSCSO) for minimizing the PAPR values utilizing the PTS mechanism. This mechanism optimally reduced the PAPR values and transmitted the information effectively. This work produced better solutions than the conventional techniques.

In 2023, Taşpınar and Aközlü [35] have integrated the PTS with the Particle Swarm Optimization (PSO) for the PAPR minimization process. The simulation solutions elaborated that the model employed in the OFDM device highly minimized the value of PAPR contrasted to the existing PTS mechanism.

In 2023, Kishore *et al.* [36] have recommended an Artificial Bee Colony Algorithm (ABCA) for minimizing the OFDM's computational complexities. An amplitude phase shift keying strategy was applied for modulation, which was more effective than the traditional strategies. Finally, the suggested work contrasted and discovered that the model produced better performances.

In 2011, Taspinar *et al.* [37] have designed a PTS-aided parallel tabu search mechanism to minimize the OFDM signal's PAPR. The suggested system was analyzed with distinct PTS mechanisms for search complexity functionalities and PAPR minimization. The outcomes revealed that the model offered good PAPR minimization.

In 2023, Priyanka *et al.* [38] have designed a PAPR minimization mechanism by applying the optimization approach named Moth Flame Optimization (MFO). Here, the MFO selected the samples automatically saving time and minimizing the PTS mechanism's computational complexity. This mechanism offered lower PAPR rates in OFDM devices.

Motivation

OFDM is a digital modulation process, in which the data are transmitted over a radio wave. In OFDM, the data are split into numerous narrowband subcarriers that are transmitted at the same time and it is suitable for reliable transmission of data. Some of the existing challenges related to existing OFDM approaches are provided in the below points.

- Existing PAPR reduction techniques introduce signal distortion, leading to degradation in BER performance. Therefore, an effective mechanism is necessary for minimizing the distortions with the support of a deep learning strategy.
- Certain PAPR reduction methods, such as selected mapping and partial transmit sequences are computationally complex, impacting real-time operation feasibility. To prevent this issue, a better strategy is necessary.
- The existing models struggle to reconstruct the transmitted information accurately since these models can't produce accurate information on the receiver side. Therefore, a better mechanism is required for eliminating this problem.
- Some traditional models implement deep learning strategies for minimizing the PAPR, yet these models don't focus on the parameter optimization that causes the performance degradation and the computational burdens. Therefore, optimizing the deep network's parameters with the support of an optimization algorithm is significant.

By focusing on these limitations in the existing works, an effective OFDM system is implemented in this research work for PAPR reduction. The benefits and challenges of existing OFDM approaches are provided in Table 1.

Table 1. *Benefits and limitations of existing OFDM approaches for reducing the PAPR*

Author [citation]	Framework	Superiorities	Downsides
Siddegowda *et al.* [20]	PTS	• It attains lower computation time. • It boosts the PAPR degradation performance.	• It suffers from extensive performance degradation.
Nguyen *et al.* [21]	PTS	• This model enhances the reliability in terms of BER.	• It suffers from high computational complexity.
Ahmad et al. [22]	DFT precoding	• It provides lower computational complexity. • It gets higher PAPR performance regarding BER.	• It is not suitable for applying in small-scale MU-MIMO-OFDM systems.

Wang *et al.* [23]	MS-SCR	• It works with a better energy consumption rate. • It achieves a higher convergence rate.	• It has a slow convergence rate due to the lack of a predetermined peak regeneration regression and appropriate scaling factor.
Lv *et al.* [24]	GA	• It efficiently minimizes out-of-band energy leaks. • It holds high resources for decreasing the PAPR reduction.	• It very poor PAPR degradation performance is observed while the amount of sub-blocks is relatively small.
Zhang and Shahrrava [25]	Class-III selected mapping	• It saves computational requirements. • It enhances the overall performance.	• The energy consumption rate is very low.
Wang *et al.* [26]	DNN	• It has higher accuracy in terms of PAPR reduction. • It occupies only less memory.	• It has a higher BER.
Kim *et al.* [19]	Deep autoencoder architecture	• It maintains BER and reduces PAPR. • It is a faster training method.	• This model does not apply to Non-Orthogonal Multiple Access (NOMA) systems.

Contributions and Innovations

The contributions of the designed OFDM system are given here.

- To implement a heuristic-assisted deep network for the degradation of PAPR in an OFDM system. This designed PAPR minimization system supports to improve the capacity of the system and also improves the transmission efficiency. Moreover, the distortions in the system have been minimized with better BER performance. The OFDM is widely utilized in practical wireless communications like television, audio broadcasting, and wireline digital communication systems.
- To develop an ODNN technique for minimizing the PAPR in OFDM. This designed ODNN is the integration of a heuristic algorithm with a DNN model, where the DNN technique's parameters are optimized with the support of I-BOA. This optimized deep network increases the PAPR reduction efficiency by minimizing the distortions. Moreover, this network increases the reliability of the system by improving the robustness of channel variations.
- To suggest the novel, I-BOA by improving the traditional BOA with its adaptive concept that improves the convergence values and also helps to explore optimal solutions. This I-BOA efficiently optimizes the hidden neurons and epoch of DNN thus helping to minimize the PAPR in an OFDM system along with better performance rates. This proposed algorithm effectively manages the transmission process in large-scale OFDM systems, optimizing performance while reducing the complexity and power necessities at both the transmitter and receiver ends.

The modules of the designed method are shown below. Module 2 specifies the system model of OFDM communication and the need for a PAPR reduction strategy. Module 3 specifies the proposed system using optimized DNN. Module 4 depicts the I-BOA-based O-DNN in the OFDM system for PAPR reduction. The resultant evaluation and summary are provided in Module 5 and Module 6.

System Model of OFDM Communication and Need for PAPR Reduction Strategy

System Model

The system model of OFDM involves dividing the available bandwidth into multiple subcarriers, where the data symbols are transmitted. The data sequences are comprised of symbols signified as N data bits. Each subcarrier is allocated with an encoder symbol that is denoted as Sh, which is generated by mapping the information. This designed model uses a constellation mapper for mapping the input data series to In-phase and Quadrature (I-Q) constellations, which is termed an encoder $e(Sh)$. Variations in the amplitude of the in-phase component are directly associated with changes in the transmitted signal's amplitude in the modulation schemes. In I-Q constellations, each point in the constellation represents a unique combination of I-Q components. By varying the amplitude and phase of these components, different symbols are transmitted over the communication channel. The receiver then decodes these symbols by analyzing the received signal's I-Q components.

Here, $e(Sh) = Z_h$ denotes the enciphered symbol of the h^{th} subcarrier Z_h that can be defined as a mapped symbol from the h^{th} statistics of the symbol. Further, through forwarding the Z_h into an inverse discrete Fourier transform, the time domain input at the Radio Frequency (RF) chain for the signal amplifier is achieved as given in Eq. (1), where the time domain signal is denoted by $z[m]$ and $0 \le m \le M-1$.

$$z[m] = \sum_{h=0}^{M-1} Z_h e^{i2\pi mh/M} \tag{1}$$

Then, the PAPR of the OFDM series $z[m]$ can be derived using Eq. (2) which is noted as $P\{z[m]\}$.

$$P\{z[m]\} = \frac{\max_{0 \le m \le M-1} |z[m]|^2}{\zeta\left[|z[m]|^2\right]} \tag{2}$$

In Eq. (2), the standard power of $z[m]$ over $0 \le m \le M-1$ is represented by the denominator. It is noted that the division of the actual segment of the time domain signal $\Re\{z[m]\}$ and of the imaginary part $\mathrm{I}\{z[m]\}$, where the higher PAPR is observed while the Gaussian distribution M is taken considerably large based on the central limit theorem [39].

The system model of the OFDM for minimizing the PAPR is provided in Fig.1. In Fig.1, the OFDM system is shown, where the transmitter and the receiver parts are included. In the transmitter part, the given data are mapped by one of the modulations (mod) mechanisms such as PSK and QAM. Further, the signal is transformed from Serial to Parallel (S/P). Next, an inverse of Fourier Transformation is employed by the Inverse Fast Fourier Transformation (IFFT) approach. The achieved signal is then transformed from Parallel to Serial (P/S) and demodulated (demo) utilizing the FFT. After that, the signal is transformed into P/S and demodulated to achieve the data outcome.

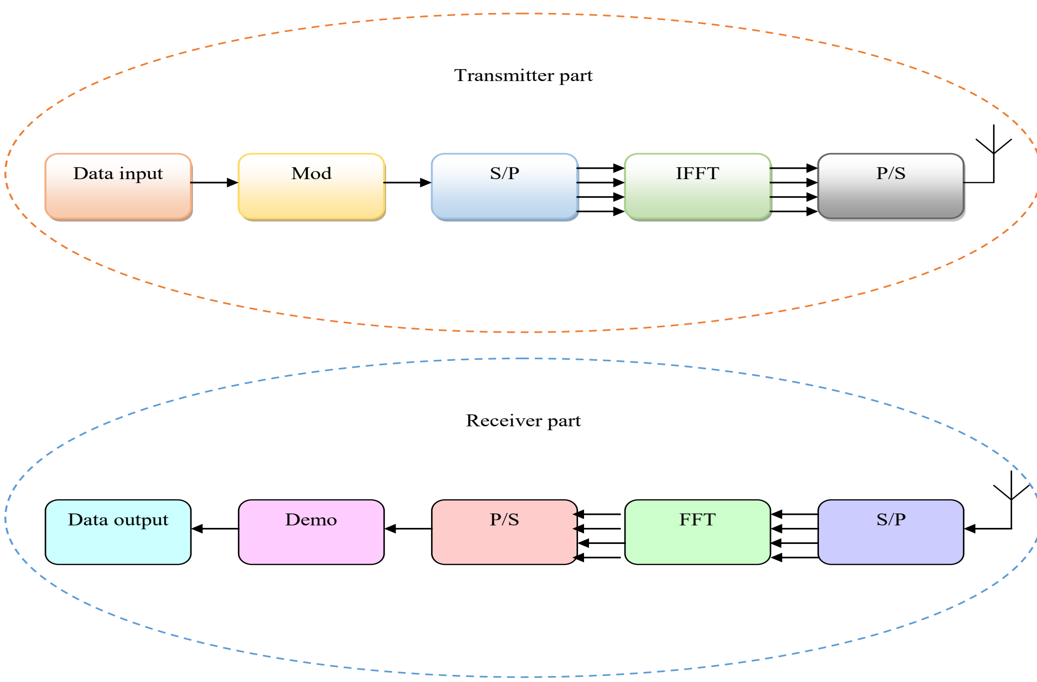


Fig. 1. *System model of OFDM for PAPR reduction*

Need for PAPR Reduction

OFDM is one of the Frequency-Division Multiplexing (FDM) schemes applied as a digital modulation approach. The data can be carried by a huge amount of closely spaced orthogonal sub-carriers [40]. High PAPR causes non-linear distortion in amplifiers that result in signal degradation and intermodulation distortion. PAPR reduction helps to diminish these distortions, boosting the overall signal quality and reducing interference [41]. The high PAPR rate of the system results in the minimization of efficiency of the RF power amplifier and higher complexity in digital-to-analog converter and analog-to-digital converter [42]. The clipping of the OFDM signal is done in the case of high PAPR and accordingly, minimizes the performance. Therefore, the transmitters of OFDM need costly linear high-power amplifiers in the huge range [43]. While enlarging the count of subcarriers, the PAPR is also increased and it creates a peak in the output envelope [44]. The common challenges of high PAPR are listed here, which motivates this research work to implement a new model.

Minimization of Performance of RF Amplifiers: RF amplifiers are nonlinear devices, and high PAPR signals cause nonlinear distortion in the amplification process. This distortion arises because of the amplifier's nonlinearity and results in signal degradation, and spectral regrowth that reduce the quality of the amplified signal. High PAPR signal needs RF amplifiers with activated large dynamic range to accommodate the peak power level. High PAPR signals hinder the amplifier's capability to accurately replicate the input signal, resulting in signal distortion, clipping, and decreased SNR. This decline in signal reliability has effects on the system performance and the quality of data transmission. The adjacent channel intervention is generated by out-of-band radiation, which influences the system functioning in the nearest bands, whereas the in-band distortion leads to degrading the system performance. Consequently, to minimize signal distortion, there is a need for a huge dynamic range of linear power amplifiers [45]. PAPR reduction capacity denotes the ability of a system to decrease the amplitude difference among the average and peak power [46].

PAPR Reduction in OFDM System using Optimized DNN-based Autoencoder

Proposed Autoencoder

The offered method uses autoencoder deep structured architecture, which is the familiar productive method in deep learning strategy. Autoencoder in designed OFDM system [47] gives various features like robustness against hardware impairments like non-linear power amplifiers, compatibility with conventional schemes, moderate training complexity owing to the short length and independent subcarrier messages, single-tap equalization, and robustness against sampling synchronization errors [48].

Assume the input, encoder, and decoder as z, $g(z)$ and $k(z)$, respectively. To minimize the loss function $\ell(z,k(g(z)))$, there is a need to train the autoencoder to generate the results $K(g(z))$. Let us consider the denoising autoencoder, from a corrupted input copy $\bar{z} = z + \varepsilon$, the original input z is reconstructed, where random noise is noted as ε , and it is used during the training stage of the deep learning model. The amount of noise applied during training affects the performance of the decoder [49]. Thus, the distribution of random noise during training is carefully chosen to avoid the excessive distortion that hinders the decoder's ability to reconstruct the transmitted signals accurately. The loss function is noted as $\|z - k(g(\bar{z}))\|_2$ and the corrupted single is reconstructed from the original signal z with the training ability of the autoencoder. Then, a stochastic gradient descent optimization algorithm [1] is used to train the autoencoder, where the equation for updating the parameter ϕ is provided in Eq. (3).

$$\phi \wedge (y+1) := \phi \wedge y - \alpha \nabla \ell(z, k(g(\bar{z}))) \tag{3}$$

Here, the term $\phi \wedge (y+1)$ is indicated as the updated parameter at iteration $y+1$, and the term $\phi \wedge y$ is specified as the current parameter at iteration y . The loss function is represented as l and the constraints utilized for producing the DNN layers are denoted as ϕ, and the learning rate is noted as α , which computes the step size of the updated value [50]. The corrupted signal is generated by merging random noise with the original signal and then it is used as the input to autoencoder [51]. The autoencoder reconstructs the original signal from the corrupted input by reducing the reconstruction error.

Operation of Deep Learning for PAPR Reduction

As the main scope of the offered OFDM method is to decrease PAPR, it uses an ODNN-based autoencoder to maximize the performance of deep learning techniques. The autoencoders learn to reconstruct and compress the OFDM signals, thus minimizing the PAPR. The autoencoders can reduce the effects of non-linear distortion in the OFDM signals. Moreover, the autoencoder can validate the channel conditions and tune the performance of the OFDM. This designed optimized DNN-based autoencoder can outperform the conventional PAPR techniques. The autoencoder demands less computational resources and also this technique becomes robust over the interference and the noise. Therefore, the autoencoder is considered in this PAPR reduction process with DNN. The DNN techniques adapt to vary system conditions of the OFDM and efficiently manage the non-linear effectiveness. The DNN provides better BER performance and enhances the system's capacity. Hence, the DNN model is considered in this process. However, the DNN model is vulnerable to noise and poorly performs in the interference. Therefore, the autoencoder is added to the DNN technique for minimizing the PAPR in the OFDM systems. This suggested model adaptively determines constellation mapping and remapping of symbols on each subcarrier, leading to enhanced system performance compared to conventional PAPR reduction schemes. The autoencoder architecture is the optimal signal-processing technique for PAPR reduction through training. Once the model is trained, this suggested model efficiently operates in real-time with a small overhead, making it suitable for practical implementation in OFDM systems. The autoencoder-based PAPR reduction scheme in OFDM is depicted in Fig. 2.

From Figure 2, the encoder and decoder [52] [53] are included with hidden layers or equal sub-blocks that are linked in tandem. Here, every sub-block is comprised of a Rectifier Linear Unit (ReLU), Batch Normalization (Batchnorm), and Fully Connected Layer (FC) which are also linked with each other. In FC, they have applied matrix application of the weights along with biases.

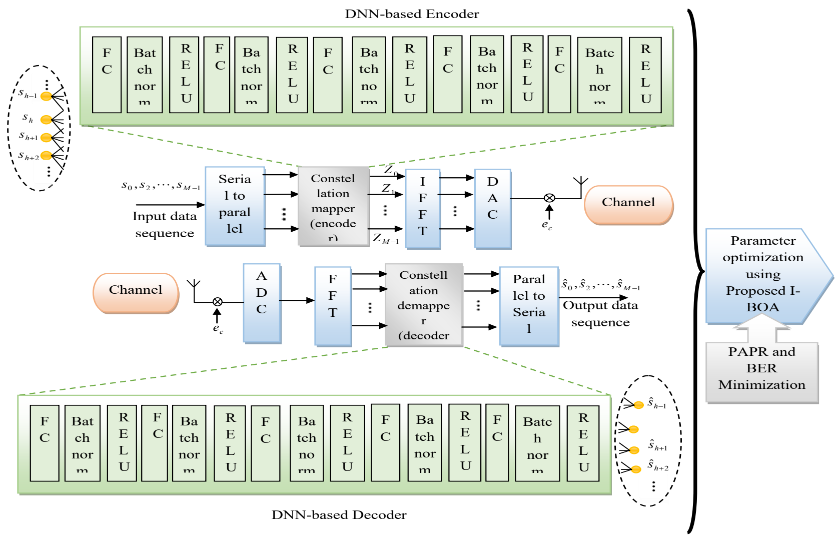


Fig. 2. *DNN-based encoder and decoder architecture for PAPR reduction in OFDM*

The input of the n^{th} FC is assumed as z_{FC}, the bias and weights for n^{th} FC are denoted as bi_n and WG_n, respectively then, the resultant of the FC is termed as op_{FC} that is determined by $op_{FC} = WG_n z_{FC} + bi_n$. Additionally, every FC includes the number of hidden nodes as 2048. The batch norm unit [54] gets the input as the result of FC, which focuses on normalizing the input of the ReLU unit, where the proposed DNN-based autoencoder with a heuristic algorithm is trained. The mathematical expression on the batch norm is derived in Eq. (4).

$$\left|op_{FC}\right|_{norm} = \chi \frac{op_{FC} - \zeta\left[op_{FC}\right]}{\sqrt{\mathrm{var}\left[op_{FC}\right] + \eta}} + \delta \tag{4}$$

In Eq. (4), a constant term that prevents the division by zero is given as η, where $\eta = 0.001$, the shift factor and scale factor are termed as δ and χ [1]. The nonlinearity in the proposed model is observed while giving the normalized value to the activation function. The designed OFDM model uses activation functions as ReLU, where the resultant of n^{th} ReLU is attained as $\max\left(\left|op_{FC}\right|_{norm}, 0\right)$.

The proposed OFDM model encodes the input data to the constellation plane including 5 sub-blocks. Further, the resultant of the encoder is derived in Eq. (5).

$$e(s) = \varphi_{\ell_e}\left(\left|WG^{e}_{\ell_e}\varphi_{\ell_e-1}\left(\ldots\varphi_1\left(\left|WG^{e}_{1}s + bi^{e}_{1}\right|_{norm}\right)\ldots\right) + bi^{de}_{\ell_{de}}\right|_{norm}\right) \tag{5}$$

Here, the bias and weights for the $\left(\ell_{de}\right)^{th}$ FC of the decoder are denoted as $bi^{de}_{\ell_{de}}$ and $WG^{e}_{\ell_e}$, respectively, and the input of the decoder is indicated as op. Consequently, at the receiver, the reconstructed symbol is shown as $\hat{s}$ that is derived in Eq. (6).

$$\hat{s} = g \circ FFT \circ \Im \circ IFFT \circ e(s) \tag{6}$$

In Eq. (6), the impacts of the wireless channel, like gradient vanishing and thermal noise are noted $\Im$. In this training, the optimized DNN-based autoencoder is implemented using I-BOA. Here, the description of DNN is given below.

The framework of the designed DNN with several number layers is explained here. DNN includes hidden layers, an output layer, and an input layer. The suitable number of layers helps in accurately learning the mapping correlation between the input and out data. This designed model can adapt different system configurations and channel conditions. The adaptive nature of the designed DNN-based deep technique helps in the reduction of noise and modulation schemes, which provide flexibility in optimizing PAPR reduction with the exact requirements of the OFDM system. The training of DNN is done through I-BOA by upgrading the weight of the nodes in the hidden layers [55]. This network continuously tries to fit the decision boundary of labeled training data owing to the increase in training iterations. The training speed of DNN can be increased by optimizing the number of suitable hidden neurons and epochs of DNN.

In Eq. (7), the average of nodes in the hidden region is calculated.

$$q = \sqrt{r + t + u} \tag{7}$$

In the abovementioned equation, the terms q, r, t and u specify the number of hidden layer nodes, the number of output layer nodes, the number of input layer nodes, and a constant value where the range of constant value is considered as $[1,10]$. The capability of irregular fitness is enabled by adding the activation function in a hidden layer of DNN, where a sigmoid is taken as an activation function FF_{sig}, which is equated in Eq. (8).

$$FF_{sig} = \frac{1}{1+e^{-z}} \tag{8}$$

In Eq. (8), the term z specifies the input data of the network that is activated FF_{MF}.

$$FF_{MF} = sigm\left(\omega_y z + \vartheta_y\right) \tag{9}$$

Here, the term ϑ is denoted as the bias among the hidden and output layer, and the vector of weight is termed as ω. Finally, the tuned DNN with I-BOA helps in improving the process by optimizing the number of suitable hidden neurons and epochs of DNN. The proposed model effectively mitigates the drawbacks associated with high PAPR in OFDM systems while maintaining low error rates. The main research motivation is to reduce the PAPR based on autoencoder for OFDM system. High PAPR involves power amplifiers to operate closer to their saturation levels, reducing their competence and potentially causing nonlinear distortion. It also increases the transmitter complexity. Hence, deep learning for efficient PAPR reduction in OFDM systems is developed, which ultimately improves system performance and addresses key challenges in wireless communication.

This designed optimized DNN-based autoencoder efficiently prevents the interference and nosie thus minimizing the PAPR in the OFDM systems. Moreover, this designed model provides flexibility in distinct configurations of the OFDM and is adaptable to vary channel conditions. The autoencoder is a symmetric, encoder-decoder-based framework. Therefore, it minimizes the hyperparameter's number. The autoencoders are self-supervised; therefore, this technique doesn't require extensive hyperparameter tuning. However, the DNN in this model demands hyperparameter tuning for providing better performance. Moreover, the DNN faces an overfitting problem due to the greater number of hyperparameters. Therefore, optimizing the parameters of DNN is necessary for the designed PAPR minimization framework. For this purpose, the I-BOA is introduced. This algorithm efficiently optimizes the parameters of DNN thus minimizing the limitations faced in this model.

Improved Billiards-inspired Optimization Algorithm-based Optimized DNN for PAPR Reduction in OFDM System

Objective Function and DNN Architecture Modification

The major scope of the designed OFDM system is to degrade the PAPR with the help of a new I-BOA algorithm. It is a dual-phase training process to determine the noise-power ratio and then learn the weights and biases of the autoencoder to minimize both PAPR and BER. The autoencoder technique utilizes a very small number of parameters thus it doesn't demand parameter tuning in this process. Moreover, it eliminates the interference and noise. However, the DNN technique employs more hyper-parameters that require careful tuning of these parameters. For this purpose, the I-BOA is designed. It can efficiently optimize the parameters in the DNN model thus helping to minimize the PAPR in OFDM systems. The objective function for this process is derived in Eq. (10).

$$Fn = \underset{\{Hn,Ep\}}{\arg\min}\left(\ell_2(s)\right) \tag{10}$$

Here, the terms Hn and Ep represent the optimized number of hidden neurons and epoch of DNN. Here, the range of Hn and Ep is taken as $[5,255]$ and $[0,1]$. The PAPR minimization is derived in Eq. (10), which is also noted as $\ell_2(s)$ and it is equated in Eq. (11).

$$\ell_2(s) = PAPR\{z(m)\} = PAPR\{IFFT(e(s;\phi_e))\} \tag{11}$$

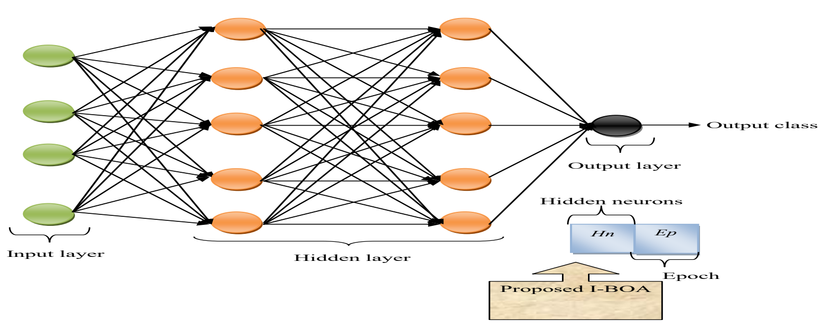


Fig. 3. *Optimized DNN architecture using the I-BOA algorithm*

It helps to achieve maximum efficiency by minimizing the PAPR in OFDM. This objective is carried out by tuning the attributes like hidden neurons and epochs of DNN. This modification with DNN architecture is diagrammatically given in Fig. 3.

Designed I-BOA

By revising the BOA, the I-BOA is implemented in this research for helping to reduce the PAPR in OFDM systems.

Purpose: A new I-BOA is implemented in this task for modifying the DNN-based autoencoder in the OFDM system, where the improvement of several suitable hidden neurons and epochs in DNN is carried out through I-BOA. This optimization process supports reducing the PAPR thus increasing the effectiveness of the system.

Novelty: The I-BOA is implemented by modifying the conventional BOA [56]. The BOA's simplicity, stability, and effective balance of exploration and exploitation, this algorithm is selected for this task. Moreover, this algorithm provides competitive outcomes for complex tasks and also gives high efficiency in discovering the optimal solutions. However, the existing BOA has some limitations. The BOA has a poor convergence rate and also takes more time to choose the optimal solutions. Therefore, for resolving this issue, the I-BOA is implemented. Here, a new concept is derived for improving convergence and speed. In this I-BOA, a new solution is formulated, where the existing solution is derived with the best solutions. The newly designed solution Ns formulation is shown in Eq. (12).

$$Ns = s + \frac{bs}{10} \tag{12}$$

In this, the newly formulated solution is specified as Ns , and the existing solution is taken as s . Moreover, the best solution which is attained from the best fitness function is considered as bs . Thus, the new solution is estimated by utilizing Eq. (12) and is applied in the BOA.

The primary steps in the I-BOA are explained as follows.

Step 1: Initialization of ball populations randomly.
Step 2: Based on the objective function, evaluation of pockets and balls position.
Step 3: Estimating the pockets and grouping the balls.
Step 4: Assign the packets to the balls, and update the ball's position.
Step 5: Escaping mechanism from local optima and validating the limitations of boundary condition.
Step 6: Estimating a new solution by Eq. (12) for improving the convergence and solution discovering speed.
Step 7: Checking the criteria of termination.

The computational complexity of this proposed algorithm is relatively small compared to traditional algorithms. When compared to other traditional models, the designed I-BOA scheme effectively manages the transmission process in OFDM systems, optimizing performance while reducing the complexity and power requirements at both the transmitter and receiver ends. The computational complexities and time complexity of the proposed model among other algorithms are provided in Table 2.

Table 2. *Computational complexity of the given designed OFDM model*

Algorithms	Computational Complexity	Time complexity (mins)
PSO	$O(Iter * N_{pop})$	11.7483
BOA	$O(Iter * (N_{pop} * N_{pop}) + N_{pop})$	9.7389
Proposed	Same as BOA	8.8376
ABC	$O(Iter * (N_{pop} + N_{pop} + Ch_{len} + N_{pop}))$	10.8478
GA	$O(Iter * N_{pop})$	10.5754

For analyzing the computational complexity of the suggested I-BOA over traditional algorithms, the big O notation is utilized. This notation is an effective component utilized to explain the algorithm's time complexity. It offers a standardized way to contrast the effectiveness of distinct algorithms concerning their performance of worst-case. Thus, the I-BOA is analyzed with the support of big O notation over existing algorithms. Here, the term $Iter$ is indicated as the current iteration and N_{pop} is represented as a number of populations. Then, the chromosome length is taken as Ch_{len} . In this developed work, the I-BOA's highest iteration is 100, and the chromosome length is 3. Moreover, the number of populations is 10. Thus, the computational complexity of the I-BOA is analyzed with the traditional algorithms.

The pseudo-code of the designed I-BOA is given in Algorithm 1.

Algorithm 1: Proposed I-BOA
Input: Epochs and hidden neuron counts in DNN
Output: Optimized epochs and hidden neuron counts in DNN
Set $N = number\ \ of\ \ balls$; $ET = escaping\ \ threshold$; $K = number\ \ of\ \ pockets$; $M = number\ \ of\ \ variables$; $it = 0$;
Initialize K pockets and $2N$ balls;
while ($it < it_{\max}$)
Estimate the packet and ball's location based on fitness function;
Upgrade the population and pocket memory;
Generate groups of normal balls and cue balls;
for every pair of ball
Choose a destination pocket by employing the strategy of roulette-wheel
End for
Upgrade the present normal ball's location;
Determine the velocity of the ordinary ball and cue ball after the collision;
Estimate the location of the present cue ball;
Upgrade the present cue ball's location;
if $rn < ET$
Reproduce a ball arbitrary dimension;
End if
Validate the limitations of boundary conditions and revise the balls if they are not present in the specific limit;
Update the new solution with a novel concept by Eq. (12);
$it = it + 1$;
End while
Return the optimal solution;

Training of ODNN for PAPR Reduction

The training of the ODNN is done to reduce the PAPR when managing the BER. This model has reconstructed the transmitted signals from the established signals without compromising BER. Secondly, the transmission signal has been generated by the designed model, which has consequently obtained a lower PAPR. The objective of BER reduction can be minimized by formulating the loss function, which is derived in Eq. (13). In this proposed scheme, the encoding and decoding of constraints for every subcarrier in an OFDM system are trained by ODNN that transmits a signal sequence with low PAPR while degrading the BER. The equation for BER is formulated in Eq. (14).

$$\ell_1(s, \hat{s}) = \left\| s - de\left(FFT\left(\Im \circ IFFT\left(e(s;\phi_e)\right) + \varepsilon\right); \phi_{de}\right) \right\|_2 \quad (13)$$

$$BER = \frac{nba\ (at\ reciever)}{tnb\ (transmitted)} \quad (14)$$

In the afore-mentioned Eq. (14), the term nba denotes the number of bits in error, and also the variable tnb is described as the total number of bits. Here, the noise at the receiver is mentioned as ε , and the parametric representation of the encoder and decoder are denoted by $e(\bullet;\phi_e)$ and $de(\bullet;\phi_{de})$, respectively. In Eq. (13), $\phi = \{WG, bi\}$, where the parametric depiction includes the biases, weight vector, and activation layers with the simple matrix operations of hidden node parameters. The loss function can be reduced by training the bias ϕ_e and weight WG of the autoencoder. So, the constellation is reliable to arbitrary channels $\Im$, which is attained with the encoder. Then, the decoder performs an effective way of decoding the constellation mapping. In addition, the PAPR can be minimized with loss function as derived in Eq. (11).

The designed model utilizes an adaptive deep-learning technique to determine the constellation mapping in each subcarrier. The training in the designed model is carried out in two phases. The initial loss function is determined in the initial phase of training with the appropriate corruption level, which is specified as the ratio between the noise power and signal power. Secondly, the learning of biases and weights of the autoencoder is done in the second stage of training with the joint loss function. By adjusting the weight parameters in the loss function, this suggested I-BOA prioritizes either PAPR reduction or BER improvement based on the specific requirements. The specific data rate and the number of bits on each subcarrier vary based on the modulation scheme used and the system requirements. These factors play a significant role in determining the overall performance and success rate of the proposed algorithm in wireless communication systems.

Calculations of Results

SimulationSetup

This OFDM system was implemented in MATLAB 2020a, and the evaluation of performance was validated regarding PAPR and statistical analysis. The performance of the PAPR was evaluated based on metrics such as BER, Complementary Cumulative Distribution Function (CCDF), and overall system characteristics. The computational overhead of the PAPR was evaluated in terms of complexity and execution time compared to other conventional schemes. This analysis has verified their performance over other heuristic algorithms like GA [57], PSO [58], ABC [59], and BOA [56] along with conventional PAPR reduction schemes like MS-SCR [23], SLM [20], and Autoencoder [19]. The simulation parameters for the given designed OFDM model are shown in Table 3. The implemented system utilizes a 2x4 MIMO configuration, utilizing a diversity gain and spatial multiplexing to attain improved reliability and data rates. The OFDM was originally designed for high-frequency radio military transceivers.

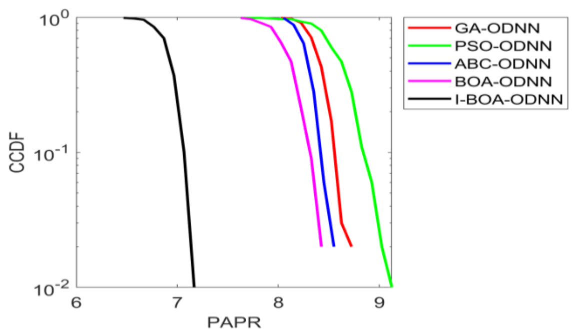
Table 3. *Simulation parameters for the designed OFDM model*

Parameters	**Values**
Channel Bandwidth	{1,2,3,4,5,6} maps to [1.4, 3, 5, 10, 15, 20] MHz
Number of sub-carriers	[64, 128, 256, 512]
SNR	1 to 10
Number of sub-blocks used in PTS methods	4
Modulation scheme	QPSK
Total number of combinations	16, 256
Route numbers used in the SLM method	2, 4, 8, 16
Number of the generated OFDM signal	1000
path delays	Integer vector of multiples of channel input sample time
showSpectrum	1 to enable, 0 to disable
numTx	{2, 4}
corrLvl	one of {'Low', 'Medium', 'High'}
modType	[1,2,3] maps to ['QPSK','16QAM','64QAM']
chanMdl	one of {'Frequency-flat static', 'User-defined'}
maxDopp	scalar
Oversampling factor	8
pathGains	vector, same length as pathDelays
contReg	{1,2,3} for >=10MHz, {2,3,4} for <10Mhz
chanEst	1 for channel estimation, 0 for ideal estimates
numRx	{1, 2, 4}
numSFrames	scalar, length of simulation

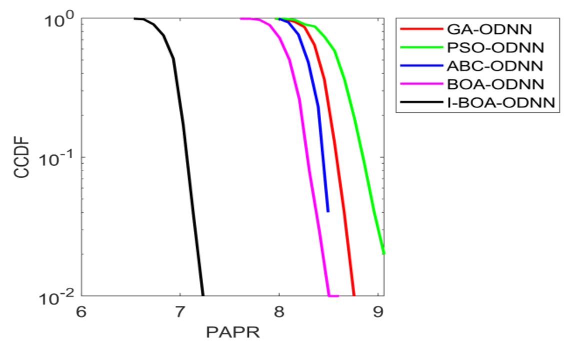
showScopes	1 to enable, 0 to disable
snrdB	scalar

Analysis of PAPR Reduction over Traditional Algorithms

The designed model regarding PAPR reduction is estimated by differing the SNR levels as given in Fig. 4. The CCDF is utilized for validating the suggested model. The CCDF is a powerful component for comparing and evaluating the distributions, especially in the context of PAPR minimization in OFDM devices. The CCDF defines the likelihood that an arbitrary factor exceeds a specific threshold. The CCDF helps to validate the efficacy of the designed model. In this developed communication system, SNR quantifies the power of background noise that distorts the signal during transmission. The proposed I-BOA helps to diminish the average power ratio of the transmitted signal. This is crucial for minimizing signal distortions, especially in OFDM systems with multiple antennas at the BS. The lower PAPR ratio is noticed with I-BOA-based ODNN while evaluating with conventional heuristic algorithms. The given PAPR reduction approach provides a good trade-off among the ability of PAPR degradation and implementation complexity, data rate loss, transmission power, and Bit-Error-Ratio (BER) performance, etc. The given PAPR performance reduction influences the computational complexity of the system. The given graph result shows the given technique enhances the performance of the OFDM system. Moreover, the suggested results show the minimum PAPR ratio. Finally, it demonstrates the lower PAPR reduction rate when evaluating with others.



(a)



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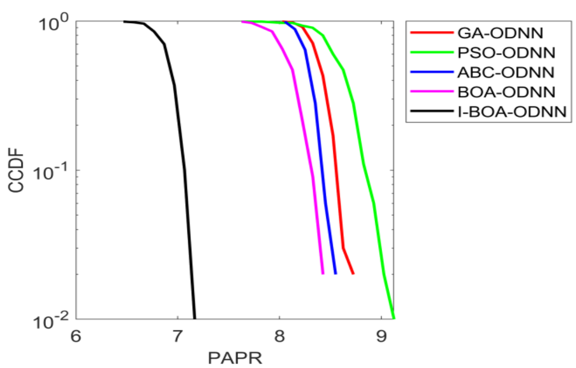

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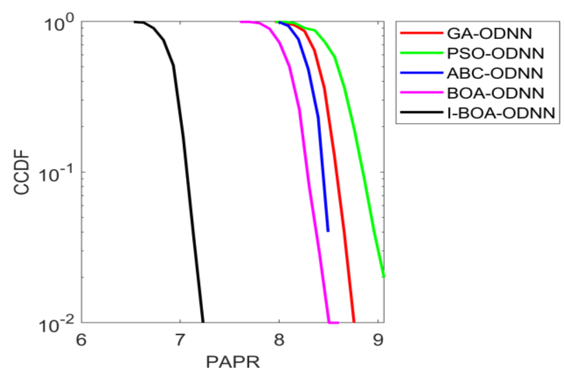

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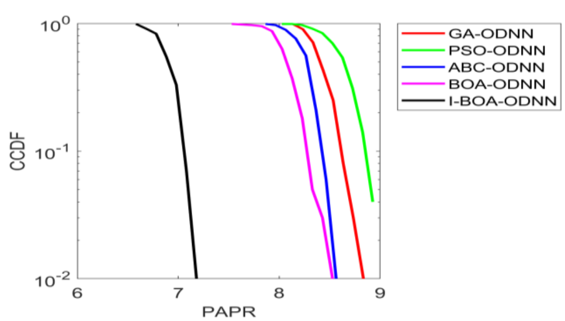
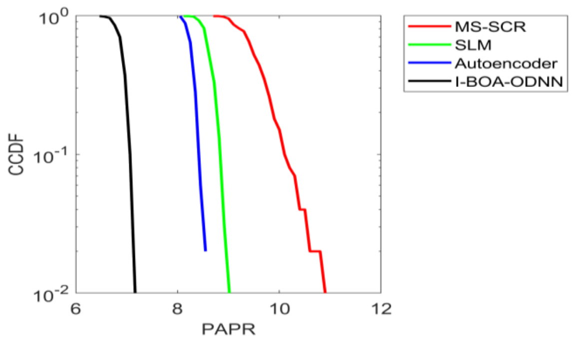


(c)

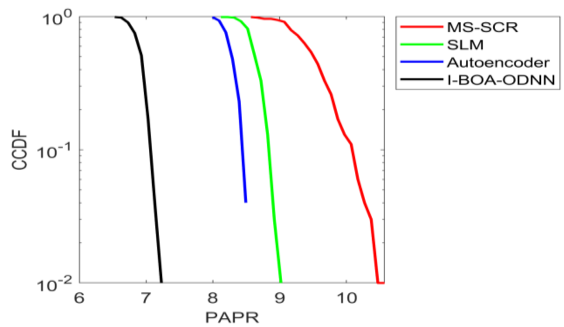
Fig. 4. *Evaluation on designed I-BOA-ODNN-based OFDM model regarding (a) SNR =0, (b) SNR =1, (c) SNR =2, (d) SNR =3, and (4) SNR =4*

Analysis of Conventional PAPR Reduction Strategies

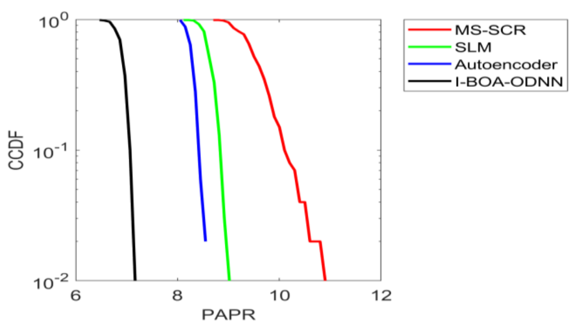
The investigation on the recommended OFDM model regarding PAPR reduction is estimated over state-of-the-art PAPR reduction schemes by varying SNR levels as shown in Fig. 5. From the given graph results, the designed I-BOA-based ODNN model attains a lower PAPR ratio.PAPR reduction strategies in OFDM systems have been extensively studied and balanced with emerging techniques like MS-SCR, SLM, and Autoencoder. Clipping is a simple and extensively used technique for PAPR reduction in OFDM systems. While effective, clipping introduces signal distortion and performance degradation, especially at high clipping levels. Moreover, MS-SCR is the least algorithm that holds a higher PAPR ratio. It degrades the OFDM system performance in the MS-SCR model. Moreover, the Autoencoder attains a second better performance. This analysis has shown that the designed I-BOA-based ODNN is superior to other existing approaches, which clearly shows that the offered method has maximized the efficiency in terms of PAPR reduction. Moreover, it has been ensured that the designed I-BOA-ODNN-based model minimizes the signal interferences and noise during the data transmission thus improving the effectiveness of the OFDM system.



(a)



(b)



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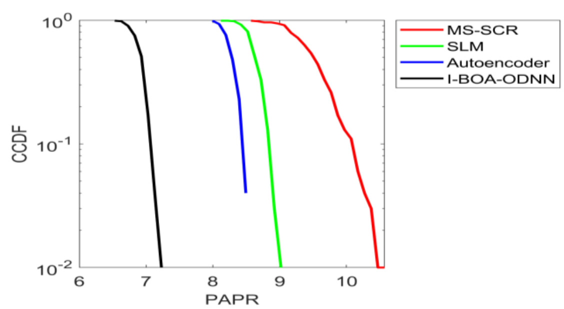

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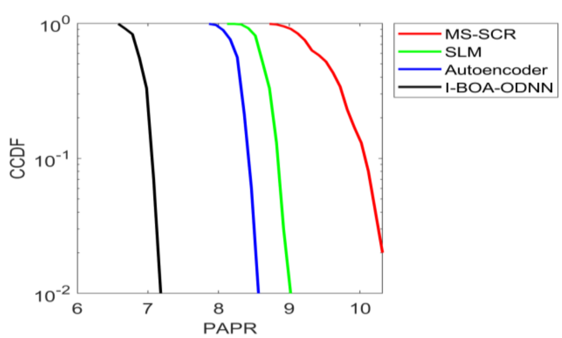

(c)

Fig. 5. *Evaluation on designed OFDM model regarding (a) SNR =0, (b) SNR =1, (c) SNR =2, (d) SNR =3, and (4) SNR =4*

Evaluation of BER

The validation of the proposed OFDM model regarding BER is done over heuristic algorithms and state-of-the-art PAPR reduction schemes by varying the SNR levels as given in Fig. 6. BER evaluation helps in determining the quality of service provided by the communication system. A low BER is essential for ensuring reliable and error-free data transmission, especially in certain applications such as wireless networks and digital communication systems. The experiment displays the minimum BER rate for the designed I-BOA-

ODNN technique while comparing it with other techniques. Throughout the graph results, it is revealed that the designed I-BOA-ODNN attains a minimum SNR ratio. Finally, the lower SNR ratio in terms of superior efficiency is noticed with other traditional techniques. BER evaluation is valuable for implementing error detection and correction mechanisms to improve the overall system reliability. Thus, it has been confirmed that the suggested I-BOA-ODNN improves the performance rates of the ODFM system than the existing techniques.

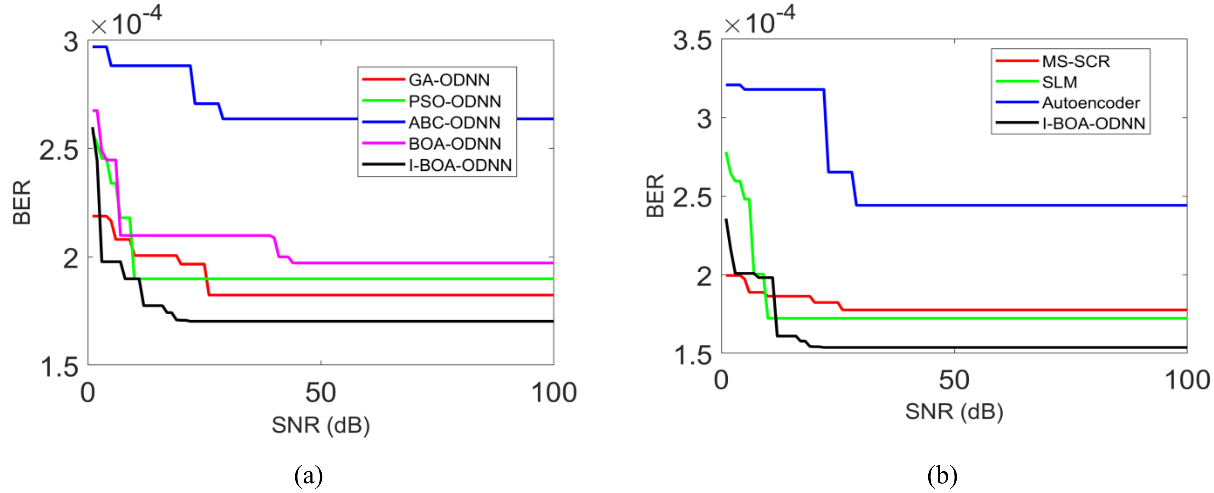

Fig. 6. *Evaluation of the designed OFDM model regarding (a) Heuristic algorithms, and (4) existing PAPR reduction schemes*

Statistical Analysis of PAPR

The performance examination of the implemented PAPR model is verified in terms of statistical analysis regarding PAPR reduction as depicted in Table 4. Here, the I-BOA algorithm's effectiveness is shown by contrasting it with the existing models for the ODNN-based PAPR minimization. The suggested I-BOA-based ODNN mechanism's performance is 17.5%, 19.3%, 16.4%, and 14.5% maximized than GA-ODNN, PSO-ODNN, ABC-ODNN, and BOA-ODNN, respectively when considering the median measure. Thus, it has been proved that the I-BOA-based ODNN achieved relatively low PAPR rates and improved performance rates than the existing algorithms.

Table 4. *Statistical analysis on the offered OFDM system for PAPR reduction over other heuristic algorithms regarding PAPR*

Algorithms	Best	Worst	Mean	Median	Standard deviation
GA-ODNN [57]	7.8167	8.9294	8.4014	8.4175	0.012597
PSO-ODNN [58]	7.6246	9.2612	8.5861	8.6063	0.022218
ABC-ODNN [59]	7.7765	8.6293	8.2826	8.3047	0.011816
BOA-ODNN [56]	7.3927	8.6945	8.0973	8.1251	0.015263
I-BOA-ODNN	6.3911	7.3555	6.9124	6.9403	0.0094359

Statistical Analysis of BER

The analysis of the implemented OFDM system regarding BER is depicted in Table 5. Owing to the attained results, the recommended I-BOA-based ODNN offers superior performance in terms of lower BER. For example, the I-BOA-based ODNN gets lower BER, which is 6.3%, 6.4%, 6.34%, and 6.37% progressed than GA-ODNN, PSO-ODNN, ABC-ODNN, and BOA-ODNN, respectively. Thus, it has been elucidated that the I-BOA-based ODNN is more effective than the conventional algorithms and thus attained improved performance in the BER. Moreover, this developed model improved the effectiveness of the designed OFDM system than the existing PAPR reduction models.

Table 5. *Analysis of the recommended OFDM system for PAPR reduction over heuristic algorithms in terms of BER*

Algorithms	Best	Worst	Mean	Median	Standard deviation
GA-ODNN [57]	0.45964	0.53646	0.49903	0.49896	0.000998
PSO-ODNN [58]	0.45964	0.52214	0.49959	0.49922	0.001795
ABC-ODNN [59]	0.45313	0.52995	0.49918	0.49948	0.001162
BOA-ODNN [56]	0.47266	0.52604	0.49945	0.4995	0.000621
I-BOA-ODNN	0.39974	0.50781	0.46759	0.46801	0.000491

Comparision with recent studies

A new literature studies are considered for the comparison and the statistical report is provided in Table 6. From this statistical report, the proposed PAPR reduction in the OFDM system enhanced its performance and efficiency for real-time operation. From the experiments, it has been elucidated that the implemented I-BOA-based ODNN mechanism relatively minimized the PAPR in the OFDM systems with improved BER rates than the traditional PAPR minimization models. Moreover, it has been observed that the suggested model helps to minimize the noise and interference in the OFDM system during the data transmission.

Table 6. *Statistical report of recommended OFDM system for PAPR reduction over recent techniques*

Algorithms	Best	Worst	Mean	Median	Standard deviation
PTS [20]	0.004857	1.005	0.10288	0.00578	0.29961
GMSK [22]	0.003955	1.004	0.10088	0.004785	0.29978
S-SCR [23]	0.002792	1.003	0.10077	0.004233	0.29959
I-BOA-ODNN	0.001	1.001	0.098688	0.001812	0.29958

Conclusion

A new PAPR reduction strategy was developed in this paper by proposing an autoencoder-based ODNN, where the hidden neuron count and epoch of DNN were tuned through an I-BOA. The proposed model aimed to minimize PAPR for the developed OFDM system. From the experimental analysis, the designed model has shown superior efficiency in terms of minimum PAPR while estimating with other algorithms. The PAPR of the I-BOA-based ODNN is 17.7%, 19.4%, 16.5%, and 14.6% reduced than GA-ODNN, PSO-ODNN, ABC-ODNN, and BOA-ODNN, respectively. Finally, the heuristic-assisted ODNN was shown superior convergence behavior. The enhancements of the designed OFDM system for the PAPR reduction model are useful for real-time applications like digital audio radio, optical light modulation, wireless local area networks, and underwater communications. In the future, the performance improvement will be conducted over a hybrid heuristic and deep learning strategy. In particular, the developed process will try to apply any one of the above-mentioned real-time applications which will help to enhance the effectiveness of the OFDM system. The investigation of MPSK schemes will be taken as future work. Improvements in training algorithms, network architectures, and optimization techniques further enhance the performance of the OFDM system. With advancements in hardware capabilities and optimization algorithms, the real-time implementation of deep learning-based PAPR reduction schemes become more feasible and leads to practical applications in various communication systems.

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Conflict of Interest: The authors declare no conflict of interest

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