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PAPR Reduction in MIMO-OFDM Using Refracted Opposition-Based Archerfish Hunting Optimization Algorithm

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Abstract: *The combination of the Multiple-Input Multiple-Output technique with Orthogonal Frequency Division Multiplexing* (*OFDM*) *is a widely used technique to improve Quality of Service* (*QoS*) *in wireless communication. However, a high Peak-to-Average Power Ratio* (*PAPR*) *in OFDM leads to signal distortion when passing through* ***a*** *High-Power Amplifier* (*HPA*) *into its nonlinear operating region. Moreover, this distortion degrades the OFDM system performance by increasing the Bit Error Rate* (*BER*)*. To address these problems, a Refracted Opposition-Based Archerfish Hunting Optimization* (*ROB-AHO*) *Algorithm is proposed to minimize PAPR in OFDM systems. The AHO Algorithm dynamically adapts to various scenarios, and the proposed ROBL helps AHO select the most suitable phase factors to minimize PAPR efficiently across operating scenarios. Experimental results demonstrate that the ROB-AHO achieved a BER of* 3.7×10^{-1} *for Signal-to-Noise Ratio* (*SNR*) *at 10 dB that outperforms prior methods, namely the Asymmetrical Auto Encoder* (*AAE*)*.*

Keywords: *Archerfish Hunting Optimization* (*AHO*)*, Bit Error Rate* (*BER*)*, Orthogonal Frequency Division Multiplexing* (*OFDM*)*, Refracted opposition-based learning, Peak-to-Average Power Ratio* (*PAPR*)*, Signal-to-Noise Ratio* (*SNR*)*.*

1. Introduction

Multiple-Input Multiple-Output (MIMO) is a fundamental technique in modern wireless communication systems that significantly enhances network coverage, energy conservation, and spectral efficiency. Orthogonal Frequency Division Multiplexing (OFDM) is another widely used modulation technique, due to its efficient high-speed data transmission over large bandwidths [1]. However, when combined in MIMO-OFDM systems, a major challenge arises: the high Peak-to-Average Power Ratio (PAPR), which restricts system performance and reduces the reliability of data transmission [2]. Therefore, PAPR reduction becomes essential in MIMO-OFDM to reduce the high peak symbols. Conventional PAPR reduction algorithms, such as Partial Transmit Scheme (PTS), clipping and filtering, selective mapping [3], and companding, have been developed and analyzed for OFDM waveforms in wireless communication [4, 5]. Among these models, the distortion-less techniques, selective mapping, and PTS are of specific interest, as they do not affect the error performance of the system [6, 7]. The PTS technique is widely used in minimizing PAPR in OFDM systems due to its distortion-free properties and low complexity [8, 9]. In OFDM, a High-Power Amplifier (HPA) is required to provide appropriate output power for reliable communication. However, the output signal represents spectral regrowth in the form of in-band signal distortions and out-of-band radiation, which increases the Bit Error Rate (BER) [10]. The extensive random search for optimal phase factors in PTS increases computational overhead and inefficient PAPR reduction [11-14]. Currently, deep learning methods are used in various applications of communication systems, namely, detection, localization, sensing, and also for channel estimation in MIMO-OFDM [15]. However, these models require additional resources, and the model with inappropriate tuning of the parameters affects the selection of phase factors [16]. In recent times, to select optimal phase factors, nature-inspired metaheuristic optimization algorithms are used in MIMO-OFDM systems for improving data transmission in wireless communication. Some of the existing optimization algorithms, such as the genetic algorithm, Non-dominated Sorting Genetic Algorithm II (NSGA-II) [17], Ant Colony Optimization (ACO), and Particle Swarm Optimization (PSO) [18], are used for PAPR reduction in the MIMO-OFDM systems [19-21]. However, these algorithms face challenges due to a lack of diversity in exploring solutions, getting stuck in local optima that lead to the selection of suboptimal phase factors, and resulting in inefficient PAPR reduction, thereby decreasing the BER in the OFDM system. The existing PAPR reduction methods used in the optimization of phase factors in the PTS technique are analyzed as follows: Abdullah et al. [22] explored an Asymmetrical Auto Encoder (AAE) method to reduce high PAPR in the Cyclic Prefix OFDM (CP-OFDM) system. The explored AAE approach was utilized to enhance communication and reduce the complexity of the CP-OFDM system by reducing PAPR. In terms of PAPR reduction, the effectiveness of the AAE was evaluated by several factors, such as various corruption levels, CP length, and up-sampling factors. However, the explored AAE method obtained a lower BER but an increase in latency that affects efficient communication in the CP-OFDM system.

Eldukhri and AI-Rayif [23] developed a Conditionally Applied Neural Network (C-ANN) to minimize the PAPR without utilizing a recovery process in OFDM. The developed C-ANN model was used to shift the location slightly according to the frequency samples without affecting phase orientation to suppress the peaks of target subcarriers. An advantage of the C-ANN method was that the optimal values of the phase factor leveraged the peak threshold obtained by the model, which helps to improve both PAPR reduction and BER levels. However, the developed C-ANN model selected inappropriate phase factors under certain conditions in PAPR reduction. Sharma et al. [24] presented an Osprey Optimization Algorithm (OOA)-based PAPR reduction method in an OFDM system. To reduce the PAPR rate efficiently, an OOA Algorithm was utilized to select the best set of phase factors in the PTS technique. However, the rapid convergence of OOA makes it suitable for efficient PAPR optimization, but the model's effectiveness in the OFDM system is limited by inappropriate phase factor selection. This greatly impacts PAPR reduction and also increases the BER. Basavaraju et al. [25] explored a Nonlinear Convergence Factor with Spotted Hyena Optimization (NCF-SHO) Algorithm to choose a phase factor for PAPR reduction in the PTS technique. The explored NCF-SHO model was employed to decrease high PAPR and find optimal phase factors in PTS in the OFDM system. The explored NCF-SHO Algorithm was utilized in the LDCP and STBC to encode and decode the signals for efficient data transmission in wireless communication. However, the explored NCF-SHO Algorithm faces challenges in minimizing PAPR due to the algorithm being stuck in local optima, which leads to selecting suboptimal phase factors. Elaage et al. [26] introduced a PAPR reduction model based on an optimization algorithm in the OFDM system for wireless communication. The introduced optimization methods for PAPR reduction were the gradient algorithm, quasi-Newton method, and conjugate gradient methods in the PTS scheme, which also included the Tone Reservation (TR) technique. The main advantage of the introduced model was the ability to minimize the distortion and improve the BER performance in the OFDM system effectively. However, the introduced PAPR optimization model had the limitation of parameter sensitivity that affected the PAPR reduction in the OFDM system. From the above literature review, it is observed that the existing PAPR reduction models have several limitations, which are mentioned as follows: suboptimal phase factor selection, slow convergence rates, and high computational demands, which greatly impact phase factor selection, resulting in high PAPR and signal distortion. To overcome these limitations, a **Refracted Opposition-Based Archerfish Hunting Optimization Algorithm (ROB-AHO Algorithm**) integrated with the PTS scheme is proposed in this research for effective PAPR reduction in a MIMO-OFDM system. The ROB technique enhanced the ability of AHO to learn and adapt to varying channel conditions and select the best set of phase factors that help reduce the PAPR value effectively. The key contributions of this research are as follows:

- The proposed **ROB-AHO Algorithm** is designed to minimize high PAPR by adapting the swarm's behavior to the evolving conditions of MIMO-OFDM systems. Additionally, the adopting ability of the AHO Algorithm in varying signal characteristics ensures more reliable and consistent PAPR reduction in wireless communication.
- The natural behaviors of shooting and jumping by archerfish for hunting prey are used to explore and refine the solutions to identify the optimal phase factor combinations.

- For enhancing the PAPR reduction.
- The proposed ROB strategy maximized the exploration ability of the AHO to focus on unexplored regions by refracting the direction to obtain promising solutions of various combinations of phase factors.

The rest of this manuscript is structured as follows: Section 2 describes the methodology. Section 3 proposes a PTS technique for PAPR reduction. Section 4 illustrates experimental results, and Section 5 concludes the manuscript.

2. Methodology

In this research, an optimization algorithm is used in the PTS for PAPR reduction. Fig. 1 represents the block diagram of the proposed PAPR reduction model. A detailed explanation of the proposed PAPR reduction framework is given in this section.

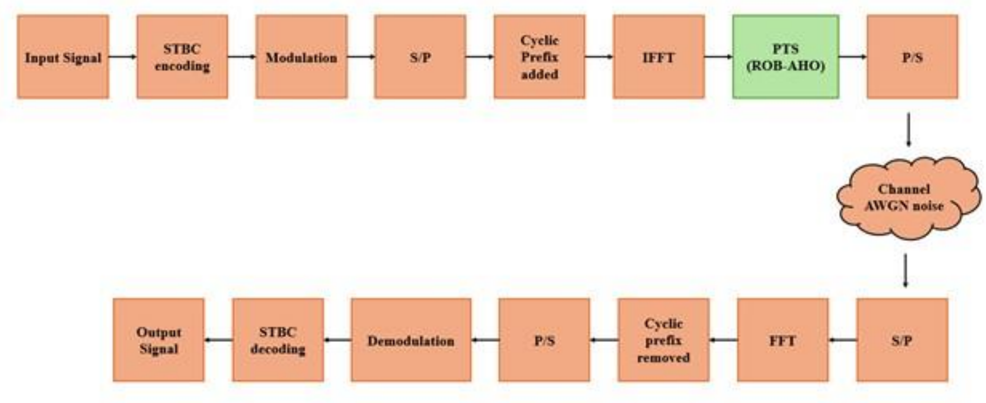

Fig. 1. Block diagram for the proposed PAPR reduction model

2.1. System model

In the OFDM system, the input bit streams are initially changed into modified baseband symbols that are further divided into individual blocks. These blocks are fed into the Serial-to-Parallel transformer (S/P) to convert the sequence of inputs into parallel. An Inverse Fast Fourier Transform (IFFT) technique is then utilized to generate the OFDM signals. After that, these data blocks are given to the CP to decrease inter-symbol interference. The Digital-to-Analogue (D/A) converter is used to convert the discrete time signal to an analogue signal, which is further amplified by an HPA. At the receiver side, an Analogue-to-Digital (A/D) convertor is used to transform the received analogue signals into digital signals, and the additional CP is removed. Subsequently, an FFT technique is used on the receiver side to obtain the original signal by using 16-QAM demapping [27]. The complex vector is used to signify the individual bandwidth in the modulated symbol. This complex vector and a sample of an OFDM signal are broadcast in discrete time with m subcarriers, which is represented as

(1) $$Y = [Y_1, Y_2, \dots, Y_{M-1}],$$

(2) $$y(m) = \frac{1}{\sqrt{M}} = \textstyle\sum_{t=0}^{M-1} Y(l)\, f^{i\frac{2\beta}{MK}lm},\ m = 0, 1, \dots, MK - 1,$$

where Y denotes the baseband vector, M indicates points in the IFFT blocks, and K represents the oversampling time. In OFDM, the PAPR represents the anticipated power ratio, which is expressed in the next equation

(3) $$\mathrm{PAPR} = \frac{\max\{|y(n)|^2\}}{F\{|y(n)|^2\}}.$$

Likewise, the performance of the OFDM system based on PAPR reduction is estimated by the Complementary Cumulative Distribution Function (CCDF), which is expressed in the equation

(4) $$\mathrm{CCDF} = \mathrm{probability}\,(\mathrm{PAPR} > \mathrm{PAPR}_0),$$

where PAPR_0 denotes the threshold value. The duration of the OFDM signal is near-zero-mean Gaussian, which is allocated to a high number of subcarriers due to the central limit theorem. Subsequently, the CCDF is represented as

(5) $$\mathrm{CCDF} - 1 - \big(1 - \exp(-\mathrm{PAPR}_0)\big)^{MK},$$

where $-\mathrm{PAPR}_0$ represents the reduced PAPR.

2.2. Partial Transmit Sequence (PTS)

In PTS, the input data frames are divided into disjoint sub-frames to maintain signal integrity while avoiding signal distortion. The objective of the PTS technique is to identify the suitable and corresponding phase factors for various phase rotations to decrease the PAPR level in the OFDM signal. The input data X The block is split into V sub-blocks, with disjoint X_v, where $v = 1, 2, \dots, V$. The partition of the input block into subframes in PTS is done as

(6) $$X = \sum_{v=1}^{V} X_v .$$

Each subcarrier position obtains a new subcarrier $X_v C^{4K}$, which establishes the original signal. Later, the IFFT operation is applied to each subframe with a l times of oversampling. Each center in the subframes is padded with $(l-1)4K$ zeros during the oversampling process. The phase factor set is mathematically represented in the equation

(7) $$\Theta = \{e^{i2\pi l/W}\ |k = 0, 1, \dots, W - 1\},\ b_v \epsilon \Theta,$$

where: b_v represents the independent rotation of partial sequences of phase factors that, according to $e^{i2\pi l/W}$ which denotes a unit complex number with a phase angle Θ as the number of allowed sets of phase factor*s*; W represents the total number of discrete phases in the set; k indicates an integer index that ranges from 0 to $W - 1$. However, the conventional techniques used in PTS face challenges and have drawbacks, which select suboptimal phase factors that greatly impact PAPR reduction.

3. Proposed AHO-based PTS

To select suitable phase factors for minimizing the PAPR and increasing the efficiency of the MIMO-OFDM system, the AHO Algorithm [28] is utilized to enhance the BER. Fig. 2 represents the workflow of the proposed AHO Algorithm in the PTS scheme for PAPR reduction in the MIMO-OFDM system. In PTS, the phase factors are indicated as complex angles belonging to a group of predefined values, such as $\{+1, \pm j\}$, where j is the imaginary unit, and generalized values from a quantized phase set, such as $\left\{0, \frac{\pi}{2}, \pi, \frac{3\pi}{2}\right\}$.

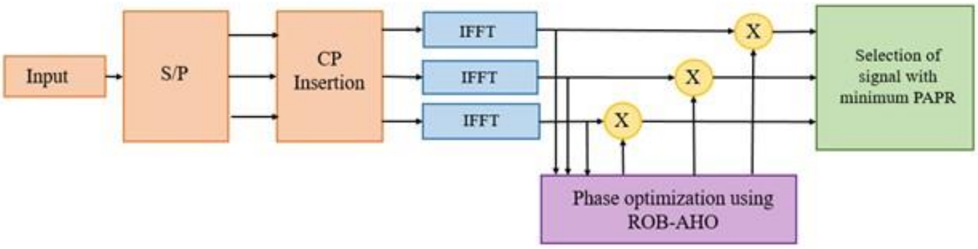

Fig. 2. Proposed AHO Algorithm in the PTS scheme based on PAPR reduction in MIMO-OFDM system

The above-mentioned phase factor values correspond to the initial set of parameters in the proposed AHO Algorithm. The initialization function of the proposed AHO Algorithm is expressed in the equation

(8) $$Y^{(a,b)} = \lambda_1 \times (Z_1^{\max} - Z_1^{\min}) + Z_1^{\min}, \ldots, \lambda_d \times \left(Z_d^{\max} - Z_d^{\min}\right) + Z_d^{\min},$$

where: $Y^{(a,b)}$ indicates the current position of the archerfish; d represents the search space dimensions; z_d indicates the uniformly distributed random counts; λ_1 and λ_d denotes a random number uniformly distributed in [0, 1] used for regulating exploration and d-th dimension.

3.1. Fitness function

Once the archerfish population is initialized in the search space, the fitness of each individual is evaluated at each iteration. In AHO, the fitness function is directly associated with the PAPR value, which is considered to choose the most appropriate phase factor for minimizing the PAPR rate and enhancing efficient communication. The mathematical formulation of the fitness function is presented in the equations

(9) $$\text{fitness function } (X)^j = \begin{cases} x \leq x_c, \\ x \geq x_g, \end{cases}$$

(10) $$(X)^j_{\text{fitness}} = \left\{\min P_{\text{err}}; \max x_{\text{optimum}},\right.$$

where: $(X)^j$ represents a potential solution or an individual during j-th iteration; x_c and x_g denotes the threshold values; $\min P_{\text{err}}$ represents the minimized probability of error, and $\max x_{\text{optimum}}$ indicates the optimal parameter.

3.2. Steps in AHO

The proposed AHO Algorithm is one of the metaheuristic optimization algorithms utilized in this research to select suitable phase factors in PTS to minimize PAPR efficiently. The proposed AHO Algorithm is inspired by the archerfish behaviors, namely, jumping and shooting to hunt prey (insects). The AHO is chosen due to its ability to achieve an effective balance between exploration and exploitation while maintaining computational efficiency. Unlike conventional metaheuristic and swarm intelligence algorithms, AHO utilizes a hunting-inspired mechanism that enables both a wide search of the solution space and precise targeting of optimal phase factors. This prevents premature convergence and local optima while ensuring faster convergence with fewer iterations, which is crucial for the computationally intensive PTS scheme. Furthermore, AHO's adaptability to varying system and channel conditions makes it more robust than classical algorithms, ensuring consistent PAPR reduction performance across different scenarios. Hence, the proposed AHO Algorithm is a more appropriate and efficient optimization algorithm when compared to other existing methods to solve PAPR reduction in OFDM systems. The objective function of the proposed AHO Algorithm is a gradient-free optimization technique to solve optimization issues in various fields effectively. The proposed AHO Algorithm is briefly explained through the main steps, which are given below.

Step 1. To select optimal phase factors in PTS, the AHO Algorithm, a metaheuristic and nature-inspired optimization algorithm, is utilized in this research. During a reasonable time, the archerfish mathematically searches for optimal solutions for problems such as PAPR reduction. The proposed AHO Algorithm represents various behaviors for global optimization, such as the shooting (attacking prey with water) and jumping behaviors of aerial insects. Initially, the archerfish is initialized as a search agent in the search space (OFDM) to find optimal phase factors.

Step 2. Random Generation and Exploration (Shooting Behaviors of Archerfish): Consequently, the initialized parameters are generated after initialization. Then, it randomly generates the search agent to find the best solution by performing exploration and exploitation processes. The archerfish utilizes shooting behavior while exploring for prey. When the prey is identified, it spits water jets at the prey to make it fall into the water's surface. An archerfish takes a lateral position while shooting to make the prey fall vertically onto the water surface, which is based on the acceleration of gravity, launch speed, and perceiving angle, respectively.

In MIMO, the prey is the phase factor, where the archerfish explores and identifies optimal phase factors in PTS using this shooting behavior by adjusting its angle.

Step 3. Exploitation (Jumping behavior): In exploitation, the archerfish refines its position, which means it moves closer to the prey and jumps to catch the prey. Similarly, the position and movement of the archerfish are defined in exploration, such as acceleration of gravity, launch speed, and perceiving angle. When the archerfish decides to capture the insect (prey), it changes its position from the current one and moves closer by using the equation

$$Y^{a,\ b+1} = Y^{a,\ b} + e^{-\left\|Y_{\text{Prey}}^{a,\ b}\right\|_2}\left(Y_{\text{Prey}}^{a,\ b} - Y^{a,\ b}\right), \tag{11}$$

where: $Y^{\langle a,\ b\rangle}$ denotes the current position of the search agent; $Y^{\langle a,\ b+1\rangle}$ represents the updated position of the search agent; $Y_{\text{Prey}}^{\langle a,\ b\rangle}$ is the position of prey; $e^{-\left\|Y_{\text{Prey}}^{a,\ b}\right\|_2}$ indicates the exponential decay term; and $\left(Y_{\text{Prey}}^{\langle a,\ b\rangle} - Y^{\langle a,\ b\rangle}\right)$ represents the directional movement vector.

Step 4. Swapping between Exploration and Exploitation phase*s*: Additionally, the swapping between the exploration and exploitation phases is based on the perceiving angle, which balances both processes to ensure the optimal phase factor is selected to reduce PAPR effectively. If extreme exploration or exploitation operations are performed during the optimization process, it may lead the model to get stuck in local optima and suffer from premature convergence. Therefore, this swapping process is important in AHO to improve optimization performance. However, there is a lack of diversity in exploration that leads to traps in local optima. To overcome this limitation, a refracted opposition-based learning technique is utilized, which helps to select optimal phase factors in PTS for reducing PAPR effectively.

3.3. ROB strategy

Recently, various metaheuristic algorithms have adopted the Opposition-Based Learning (OBL) strategy to enhance the exploration ability of the model by generating opposite solutions to increase the chances of finding optimal results. However, the standard OBL strategy has certain drawbacks, which include an imbalance between local and global search capabilities and limited adaptability to dynamic environments. These limitations often reduce population diversity, causing the algorithm to get trapped in local optima and leading to premature convergence. Consequently, a Refracted Opposition-Based (ROB) learning technique is proposed to mitigate local optima and enhance the lack of diversity in the exploration phase of the proposed AHO Algorithm. The proposed ROBL strategy utilizes the principles of both OBL and the refraction law of light to explore more optimal solutions for reducing PAPR in MIMO. The mathematical representation of the proposed ROBL strategy is given in the equations

$$Y_j^{a,\ b+1} = \text{mid}_j + \frac{\text{mid}_j - Y_j^{a,\ b}}{\sigma}, \tag{12}$$

$$\text{mid}_j = \frac{Y_j^{\text{best},\ b} + Y_j^{\text{worst},\ b}}{2}, \tag{13}$$

$$\sigma = \frac{m}{m^*}, \tag{14}$$

where: $Y_j^{\langle a,\ b\rangle}$ indicates the position of the archerfish in the j-th dimension at iteration b; $Y_j^{\langle a,\ b+1\rangle}$ denotes the refracted position of the archerfish; mid_j represents the dynamic midpoint between the best and worst solutions; σ indicates the ratio that controls the refracted distance; m and m^* denote the lengths of the incident and the refracted rays, respectively. The advantage of this ROB strategy is that it reflects the current solution across a dynamic midpoint (not static bounds), which pushes individuals to search unexplored regions of the search space. This increases the diversity in the exploration phase and decreases the risk of selecting suboptimal solutions (phase factors), which is a major problem when minimizing PAPR. Algorithm 1 bellow depicts the overall PAPR reduction process using **ROB-AHO** in a MIMO-OFDM system.

In MIMO-OFDM, the proposed **ROB-AHO** is employed to select the most appropriate phase rotation factors across multiple spatial layers to reduce PAPR. The proposed optimization-based PAPR reduction model iteratively refines through adaptive exploration with the ROB strategy to identify the complex high-dimensional search space of MIMO sub-blocks. By dynamically balancing exploration and exploitation, the AHO Algorithm avoids the local optima and identifies the near-optimal phase combination, which increases destructive interference between peak signals. This identification of optimal phase factors in PTS helps to reduce the statistical probability of high-power peaks across all antennas simultaneously, which allows the model's power amplifier to operate with reduced power. Due to the reduction of PAPR, it results in high power efficiency, minimized non-linear distortion, and improved overall Signal-to-Noise Ratio **(**SNR) for efficient data transmission.

Algorithm 1.

Input: OFDM signal $x_{f\mathrm{req}}$, *n*umber of sub-blocks d, *p*hase set $\{\theta, \pi/2, \pi, 3\pi/2\}$, population size NP, maximum iterations MaxIter.

Output: Optimal phase factors best_phase_vector, minimized the PAPR value

Step 1. Start

Step 2. Initialize the archerfish population $y[a]$ randomly within $[0, 2\pi]$ for all $a = 1 - NP$

Step 3. Estimate $y[a]$ to the nearest value in the predefined phase set.

Step 4. For each candidate, reconstruct the OFDM signal with the selected phase factors and evaluate the PAPR value.

Step 5. Select the best (minimum PAPR) and worst (maximum PAPR) solutions as y_{best} and y_{worst}.

Step 6. Repeat until maximum iterations MaxIter is reached:

Step 7. For each archerfish a in the population, do the following:

Step 8. Decide whether to explore (shoot)/exploit (jump) based on the perceived probability.

Step 9. If exploration, then:

Step 10. Update position toward a random prey (candidate) using Equation (11).

Step 11. Else exploitation:

Step 12. Update position towards the best prey (solution) using jumping Equation (12).

Step 13. End if

Step 14. Add a small perturbation to maintain diversity.

Step 15. Apply the ROB strategy, which reflects the candidate across a dynamic midpoint between the best and worst solutions to search unexplored regions.

Step 16. Estimate the updated solutions to the phase set and compute the PAPR value.

Step 17. If new PAPR < current PAPR, then

Step 18. Replace the current solution if the new one gives lower PAPR.

Step 19. End If

Step 20. End For

Step 21. Update the global best and worst solutions after each iteration.

Step 22. Until a stop condition is attained.

Step 23. Return the best_phase_vector and minimized the PAPR value.

Step 24. End

4. Results and discussion

In this section, performance analysis of the **ROB-AHO** method used to optimize the PAPR in MIMO-OFDM systems is evaluated and discussed. The simulations were conducted in MATLAB R2021b (Version 9.11) on a system equipped with an i5 processor and 6 GB RAM. Performance analysis of the proposed PAPR reduction method is carried out using three key evaluation measures, namely, BER, Symbol Error Rate (SER), and CCDF, respectively. To validate the **ROB-AHO** effectiveness, PTS is compared against existing optimization techniques, including PSO, ACO, Grey Wolf Optimization (GWO), and the standard AHO. Table 1 depicts simulation settings of the proposed **ROB-AHO** Algorithm utilized to minimize PAPR in the OFDM system.

Table 1. Simulation settings of the proposed **ROB-AHO** Algorithm

Parameter	Value
Subcarrier numbers of OFDM	1024
Transmit antenna numbers	4
Receiver antenna numbers	2
Modulation	16-QAM
Iteration numbers	50
AWGN variance	0.01

4.1. Qualitative and quantitative analysis

The *p*erformance of the proposed PAPR reduction model in the MIMO-OFDM systems is assessed through both quantitative and qualitative analysis. Tables 2, 3, and 4 and Figs 3 and 4 represent the effectiveness of **ROB-AHO** in PAPR reduction using key performance metrics such as BER, PAPR, and CCDF, respectively.

Table 2 represents the BER performance of the **ROB-AHO** model at different SNR levels, such as SNR=10, 20, and 30 dB, with the conventional methods. From the results, it is clear that the proposed PAPR reduction model achieves the lowest BER at various SNR levels, which represents the model's ability to select optimal factors. Unlike the classical algorithms such as PSO, BWO, and OPA, which stagnate and get stuck in local optima, AHO with ROB enhances the exploration ability of the algorithm, which leads to achieving superior results even at high SNR levels.

Table 2. Bit Error Rate (BER) performance of different optimization methods at SNR = 10, 20, and 30 dB

Method	BER at SNR = 10 dB	BER at SNR = 20 dB	BER at SNR = 30 dB
PSO	8.20×10^{-2}	1.50×10^{-2}	2.30×10^{-3}
BWO	7.50×10^{-2}	1.30×10^{-2}	1.90×10^{-3}
OPA	6.80×10^{-2}	1.10×10^{-2}	1.50×10^{-3}
AHO	5.20×10^{-2}	8.00×10^{-3}	9.00×10^{-4}
Proposed **ROB-AHO**	4.30×10^{-2}	4.80×10^{-3}	3.50×10^{-4}

The performance of the **ROB-AHO**-based PAPR reduction model is evaluated at a low SNR level with the state-of-the-art methods represented in Table 3. At SNR=0 dB, BER for 16-QAM typically ranges from 0.2 to 0.4 due to noise dominance. The proposed **ROB-AHO** model achieves 22% BER, which represents its superior phase factor optimization in the MIMO-OFDM when compared to existing PAPR reduction methods. From the results, it is clear that the **ROB-AHO** model outperforms the conventional methods because at very low SNR levels, the error rates typically increase, but the performance of the proposed model attained a lower error rate. Due to the robust learning technique, it helps the AHO Algorithm more than the conventional AHO Algorithm, which degrades significantly. This integration of **ROB-AHO** highlights its resilience in the noisy channel conditions.

Table 3. Comparative BER performance of the proposed **ROB-AHO** with classical optimization methods at low SNR (SNR = 0 dB)

Method	BER at SNR= 0 dB
PSO	0.32
BWO	0.30
OPA	0.28
AHO	0.25
Proposed **ROB-AHO**	0.22

The SER performance evaluation of the proposed **ROB-AHO** method at various SNR levels is represented in Table 4. According to the results obtained by the proposed PAPR reduction model, which consistently achieves low SER when compared to the conventional optimization algorithms used for PAPR reduction.

i) At SNR = 10 dB. At SNR 10 dB, the signal is heavily influenced by noise. Whereas the proposed **ROB-AHO** model achieved an SER of 5.80×10^{-2}, which is significantly lower than existing conventional models such as PSO and BWO. These algorithms often suffer from “premature convergence”, which means they often get trapped in local optima. In the context of PTS, this results in poor phase factor selection, which leads to the PAPR remaining high and forcing the signal into the non-linear region of the HPA. This causes in-band distortion, which, when combined with high 10 dB noise, leads to the high error rates seen in PSO/BWO. **ROB-AHO** uses opposition-based learning to explore the search space more effectively, avoiding these local traps.

ii) At SNR = 20 dB. At 20 dB, the proposed model achieves 6.00×10^{-3}, which is lower than the existing algorithm, OPA. As the channel noise decreases, the primary source of error shifts from thermal noise to Inter-Symbol Interference (ISI), which is caused by HPA non-linearity. The integration of the ROB strategy allows the AHO Algorithm to refine its search for the global optimum. By finding the optimal phase factors, the proposed model minimizes the signal peaks more effectively than OPA and ensures that the signal stays within the linear amplification range, thereby drastically reducing the SER.

iii) At SNR = 30 dB. At 30 dB, the proposed model, whileremainst SER of 4.00×10^{-4}, whremains at 3.00×10^{-3}. The performance of PSO and BWO failed to achieve low error rates because of their architectural constraints that limit the precision of results, which leads to a higher SER. The **ROB-AHO** model's superior convergence allows it to identify the most precise phase shifts for the 16-QAM, which maintain a lower PAPR rate. The result confirms that the proposed method is not only faster but also provides a more stable communication link.

Table 4. SER performance of different optimization methods at SNR=10, 20, and 30 dB (16-QAM, MIMO-OFDM)

Method	SER		
	SNR = 10 dB	SNR = 20 dB	SNR = 30 dB
PSO	1.20×10^{-1}	2.00×10^{-2}	3.00×10^{-3}
BWO	1.10×10^{-1}	1.80×10^{-2}	2.50×10^{-3}
OPA	9.50×10^{-2}	1.60×10^{-2}	2.00×10^{-3}
AHO	7.00×10^{-2}	1.10×10^{-2}	9.00×10^{-4}
Proposed **ROB-AHO**	5.80×10^{-2}	6.00×10^{-3}	4.00×10^{-4}

Computation complexity analysis of the **ROB-AHO** model used in PAPR reduction for MIMO-OFDM systems is represented in Table 5. From the results, it is confirmed that the conventional methods have high computational complexity $O(N_\text{p} \times I)$. Unlike conventional methods, which require 32-45 iterations to converge, the proposed **ROB-AHO** model only performs 18 iterations and converges with a complexity of $O\ (N_\text{p} \times I_\text{r})$, where I_r = reduced iterations and $I_\text{r} < I$. Moreover, the proposed PAPR reduction method attained 45% lower computation time while maintaining superior BER, SER, and CCDF performance than the conventional approaches utilized in MIMO-OFDM.

Table 5. Computational complexity analysis of the proposed **ROB-AHO**-based PAPR reduction in MIMO-OFDM

Method	Avg. iterations to converge	Relative computation time (normalized)	Complexity order
PSO	45	1.00 (baseline)	$O(N_\text{p} \times I)$
BWO	42	0.95	$O(N_\text{p} \times I)$
OPA	38	0.90	$O(N_\text{p} \times I)$
AHO	32	0.75	$O(N_\text{p} \times I)$
Proposed **ROB-AHO**	18	0.55	$O(N_\text{p} \times I_\text{r}), I_\text{r} < I$

where N_p = population size and I = number of iterations.

Fig. 3 represents the performance of **ROB-AHO** in terms of CCDF (%) vs PAPR (dB) with conventional algorithms. The CCDF curve represents the proposed **ROB-AHO** Algorithm achieving significantly lower PAPR across thresholds (2-10 dB) when compared to conventional optimization algorithms such as PSO, BWO, OPA, and AHO. Since the traditional optimizers, namely, PSO and BWO, suffer from premature convergence, which leads to attaining high CCDF values, while the OPA performs better but still lacks strong diversity. The ROB learning strategy with the AHO Algorithm enhances diversity and prevents the model from selecting suboptimal phase factor selection. The integration of ROBL with AHO leads to the achievement of a smoother CCDF curve with minimized PAPR, which improves the efficiency of the amplifier and signal quality in the MIMO-OFDM system.

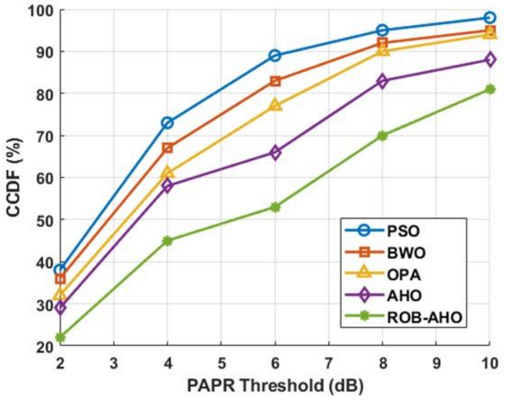

Fig. 3. Performance evaluation of **ROB-AHO** based on CCDF vs PAPR (dB)

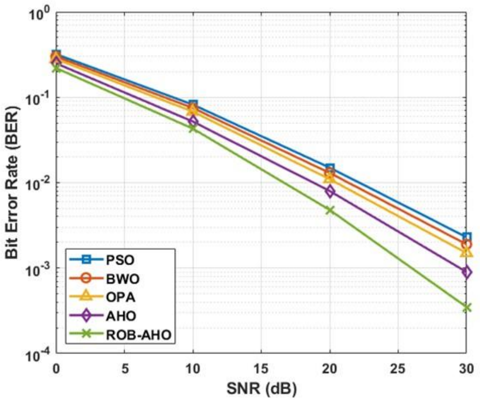

Fig. 4. The BER Performance Comparison of Optimization Methods at SNR (30 dB)

Fig. 4 illustrates the BER performance comparison of various optimization methods at SNR (30 dB) in the MIMO-OFDM system. From the results, it is clear that the **ROB-AHO**-based PAPR reduction model achieves the lowest error rate across all SNR values when compared to classical optimization algorithms. At low SNR (10 dB), the existing metaheuristic algorithms show higher BER due to limited exploration and poor phase factor optimization. When SNR increases, all the existing methods improve, but the **ROB-AHO** Algorithm converges faster due to its effective opposite-based learning. This incorporation of a learning strategy with the AHO Algorithm enables better phase factor selection, which leads to achieving superior BER reduction even at high SNR levels. Hence, from the obtained BER results at lower SNR levels, the **ROB-AHO** model ensures reliable transmission in MIMO-OFDM systems.

4.2. Comparative analysis

In this section, a comparative study of the proposed **ROB-AHO** Algorithm against existing PTS-based phase factor optimization methods under different scenarios. The evaluation is carried out using BER and SNR as key performance metrics. Tables 6 and 7 summarize the evaluation scenarios and the comparative results with the AAE [20] model. In Table 7, $\lambda = 0.1$, AAE [20] represents the corruption level (noise/distortion) added to the input signal. The **ROB-AHO** Algorithm is used for fine-tuning, which controls search step size and initialization spread. By keeping low $\lambda = 0.1$ the proposed algorithm makes fine-tuned adjustments to the phase factors, which leads to achieving lower BER results when compared to the AAE model.

Table 6. Represents simulation scenarios of existing PAPR reduction models in the OFDM system

Parameter	Simulation scenarios		
	AAE [20]	C-ANN [21]	OOA [22]
Modulation	16-QAM	16-QAM	16-QAM
Channel	Rayleigh fading with AWGN	Rayleigh channel	Rayleigh fading

Table 7. Comparative study of **ROB-AHO** with BER with $\lambda = 0.1$

Author	Method	BER		
		SNR = 10 dB	SNR = 20 dB	SNR= 30 dB
Abdullah et al. [22]	AAE	4×10^{-1}	9×10^{-1}	8×10^{-1}
Proposed Method	**ROB-AHO**	7×10^{-1}	4×10^{-1}	2×10^{-1}

Tables 8 and 9 illustrate a comparative study of the proposed algorithm with C-ANN [21]. The evaluation is carried out using CCDF, and SNR metrics are considered to estimate the PAPR value attained by the proposed model in the OFDM system. From the results in Table 8, at SNR = 30 dB, BER for 16-QAM typically ranges < 10^{-4} for the advanced methods. The **ROB-AHO** model attained a BER of 3.50×10^{-4}, which shows its superior performance in PAPR reduction.

Table 8. Comparative evaluation of **ROB-AHO** at SNR = 0 dB

Author	Method	BER
Eldukhri and Al-Rayif [23]	C-ANN	9.00×10^{-4}
Proposed method	**ROB-AHO**	3.50×10^{-4}

Table 9. Comparative analysis of **ROB-AHO** at PAPR = 10^{-3} dB

Author	Method	CCDF (%) @ PAPR = 10^{-3} dB
Eldukhri and Al-Rayif [23]	C-ANN	5.5
Proposed method	**ROB-AHO**	5.1

Table 10 presents the comparative results of **ROB-AHO** with OOA [22]. The evaluation is carried out at CCDF = 10 dB; it typically ranges between 1 and 10% for **ROB-AHO**, and it is 5.1%, which is a significant improvement over the C-ANN approach.

Table 10. Comparative study of **ROB-AHO** vs OOA [22] in terms of iterations

Method	PAPR (dB)				
	2	4	6	8	10
OOA [22]	34	50	69	88	93
Proposed **ROB-AHO**	22	45	53	70	81

4.3. Discussion

The proposed **ROB-AHO** Algorithm demonstrates a superior performance in reducing PAPR when applied with the PTS technique in MIMO-OFDM systems. In contrast, the previous PTS techniques face difficulties, which are discussed as follows: the AAE [20] approach with increased delay affects efficient communication in the CP-OFDM system. The C-ANN [21] model suffers from inappropriate hyperparameter tuning that makes the model difficult to identify optimal phase factors under certain conditions. Due to a lack of adaptability and computational complexity, the OOA [22] method faces struggles in efficient PAPR reduction. The comparative analysis clearly shows that existing approaches, such as AAE [20], C-ANN [21], and OOA [22], obtained high BER and PAPR as the models suffered from limitations such as weak exploration capability, premature convergence, and slower convergence in iterative optimization. For example, AAE provides only marginal BER improvements across SNR levels, while C-ANN, though effective, shows lower robustness under high PAPR conditions. Similarly, OOA requires more iterations to reach acceptable PAPR reduction, making it computationally inefficient. To address these issues, an **ROB-AHO** is proposed to minimize the high PAPR rate by selecting appropriate phase factors. The search ability of archerfish through jumping and shooting selects optimal phase factors and also effectively reduces PAPR, thereby preserving the quality of transmitted signals. Unlike existing methods, the proposed ROBL strategy improved the search diversity of the AHO Algorithm and maintained a balance between exploration and exploitation, achieving lower BER across varying SNR levels and enhancing PAPR reduction with fewer iterations. This leads to faster convergence, improved reliability, and greater efficiency in MIMO-OFDM systems by optimizing power utilization without introducing signal distortion.

5. Conclusion

In this research, an improved optimization algorithm known as **ROB-AHO** is proposed within the PTS for minimizing PAPR in the MIMO-OFDM system. Here, the OFDM system with high PAPR reduces the efficiency of the amplifier and causes distortion. Hence, PAPR reduction is crucial to enhance power efficiency and transmission quality. Also, most of the existing research used for PAPR reduction was based on the PTS scheme by selecting optimal phase factors.

However, the various traditional models utilized in PTS face difficulties in the selection of suitable phase factors that lead to affecting PAPR reduction. Thus, the **ROB-AHO** model is proposed to determine the most appropriate set of phase factors for minimizing the PAPR effectively. In this phase, factor selection, the natural behaviors of the AHO Algorithm, such as shooting and jumping behaviors, allow the model to search for better phase factors in PTS. The limitations, such as a lack of diversity and parameter insensitivity, lead to selecting suboptimal results that greatly impact PAPR reduction. To solve this issue, an improvisation ROBL technique is integrated with the AHO Algorithm, which assists the search agents in exploring the unexplored regions in the solution space. This integration of learning strategy improved the identification of ideal phase factors to reduce the PAPR effectively in MIMO-OFDM. Due to these advantages, the proposed **ROB-AHO** model attained a BER = 3.7×10^{-1} for SNR = 10 dB and a PAPR = 2 dB after 26 iterations, which is lower than the existing approaches. In the future, advanced PAPR reduction techniques will be developed to enhance the signal transmission quality in MIMO-OFDM systems.

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