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Inner Selection Learning Strategy with Chameleon Swarm Optimization Algorithm Based PAPR Reduction in MIMO-OFDM

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Abstract: The Multiple Input Multiple Output (MIMO) technique is a reliable method integrated with the Orthogonal Frequency Division Multiplexing (OFDM) scheme to deliver enhanced Quality of Service (QoS) for multimedia wireless communication. However, the high Peak-to-Average Power Ratio (PAPR) in OFDM signals causes signal distortion in the nonlinear region of the High-Power Amplifier (HPA), leading to an increase in the Bit Error Rate (BER). To address these issues, an Inner Selection Learning (ISL) strategy is employed alongside the Chameleon Swarm Optimization (CSO) algorithm for PAPR reduction in OFDM. The proposed ISL strategy helps minimize the search space for phase factor combinations, making the Partial Transmit Sequence (PTS) scheme more computationally feasible without compromising PAPR reduction performance. The CSO algorithm dynamically optimizes the phase factors and adapts to varying channel conditions and system environments. The integration of ISL with the CSO algorithm allows the system to select the best phase factors to minimize PAPR under diverse operating conditions. Experimental results show that the proposed method achieved a Bit Error Rate (BER) of 4.3 and a PAPR of 2 dB after 26 iterations, outperforming existing approaches such as Ant Colony Optimization (ACO) and the Osprey Optimization Algorithm (OOA).

Keywords: Chameleon swarm optimization, High-power amplifier, Inner selection learning strategy, Orthogonal frequency division multiplexing, Peak-to-average power ratio.

1. Introduction

Multiple-Input Multiple-Output (MIMO) is essential for supporting an extensive range of services in wireless communication systems, aiming to achieve higher spectral efficiency, wider network coverage, and more efficient energy use. Orthogonal Frequency Division Multiplexing (OFDM) is a usually employed as modulation technique in wireless communication systems because of its capability to transmit high-speed data with relatively large bandwidth. OFDM plays a vital role in enabling high data rate transmission, improving spectrum efficiency, and providing high robustness against Inter-Symbol Interference (ISI) in communication systems [1-3]. The design of communication systems, especially in multimedia applications, primarily focuses on power consumption and energy efficiency. OFDM is an advanced modulation technique that is a key technology for fifth-generation (5G) cellular networks and the IEEE 802.11ax (Wi-Fi 6) standard [4]. OFDMA, a variation of OFDM, divides the frequency resources into resource units (RUs), each occupying a certain number of subcarriers [5, 6]. However, OFDM systems often suffer from a high Peak-to-Average Power Ratio (PAPR), which reduces the efficiency of radio frequency power amplifiers and degrades overall system performance [7]. In existing research, several techniques have been proposed to mitigate high PAPR problem, categorized into distortion-based methods such as clipping, and peak windowing and filtering, which are used to minimize large signal peaks [8, 9].

However, these techniques increase both in-band and out-of-band distortion. To mitigate this, Selected Mapping (SLM), Partial Transmit Sequence (PTS), and corresponding set sequence-based reduction methods are employed to lower PAPR levels [10-12]. One technique for reducing PAPR without compromising information, and which can be easily recovered by the receiver, is by adjusting the frequency domain signals. The PTS method offers the highest efficiency and the least distortion scheme for PAPR reduction in OFDM structures [13]. Therefore, the PTS approach is selected for the MIMO-OFDM system. In the PTS method, the input information block is divided into numerous independent sub-blocks. The Inverse Fast Fourier Transform (IFFT) is applied to each sub-block, and the time-domain signals are multiplied by a segment rotation factor accordingly. The principle of the PTS scheme is to select segment factors that minimize the PAPR of the combined signal of each sub-block [14]. In PTS, the selection of optimal phase factors and phase rotation elements across various sub-blocks increases the complexity, and sub-optimal block partitioning limits the PAPR reduction benefits [15]. To address these limitations, an Inner Selection Learning Strategy with a Chameleon Swarm Optimization (ISL-CSO) algorithm is proposed for more effective PAPR reduction using the PTS technique in a MIMO-OFDM system. The main contribution of this research is:

- An ISL-CSO is proposed for PAPR reduction which adjusts the swarm’s behavior based on dynamic environments of MIMO-OFDM, the algorithm adapts to varying signal characteristics in communication systems that result in reliable PAPR reduction.
- The adaptability of the CSO algorithm with an inner selection strategy selects optimal phase factors in each iteration, to ensure a global solution that reduces PAPR, which is crucial in a communication system
- The proposed ISL strategy enhances the exploitation ability of CSO by focusing on promising solutions within a selected population, allowing more effective exploration of various combinations of phase factors for PAPR reduction.

This research paper is organized in the following format: Section 2 describes literature review. Section 3 explains the details of the proposed methodology. Section 4 illustrates results and the discussion and conclusion of this research paper are given in Section 5.

2. Literature review

The advantages and limitations of methods utilized for phase optimization in the PTS scheme of the OFDM system are discussed below:

Kumar [16] designed a PAPR reduction method based on Ant Colony Optimization (ACO) for offset quadrature amplitude modulation-based filter bank multi-carrier. The designed ACO algorithm was combined with the PTS technique to minimize PAPR in each sub-block and optimized the usage of each unit effectively. An advantage of the designed ACO algorithm is reduced PAPR which helps to improve the efficiency of power amplifiers and minimize the signal distortions. However, the designed ACO model has a slow convergence rate that affects the processing speed of the communication system.

Jothi and Chandrasekar [17] developed an efficient Modified Dragonfly Optimization (MDO) based MIMO-OFDM for PAPR reduction. The MDO was developed to minimize power consumption of mobile communication systems and optimize their energy efficiency. The main advantage of the developed MDO model was optimized transmission strategies that minimized Bit Error Rate (BER) and led to enhanced signal quality. However, the iterative nature of the MDO algorithm requires an extensive computational resource, which makes the developed MDOC model inappropriate for certain conditions in PAPR reduction.

Sharma [18] presented a PAPR reduction method in the OFDM system based on the Osprey Optimization Algorithm (OOA). To minimize high computational costs and PAPR of OFDM systems, the presented OOA was utilized for reduction of OFDM systems with high PAPR and computational costs. An advantage of OOA algorithm utilized for PAPR reduction has a better convergence rate that makes the OOA model more suitable for reducing PAPR in 6G systems. However, the integration of OOA for PAPR reduction in OFDM systems requires additional implementation efforts, especially in terms of algorithm design and adaptation which increases the complexity of communication systems.

Gajulapalli and Gnanadhas [19] explored a PAPR and BER reduction model in MIMO-OFDM based on Hybrid Moth Flame -Improved Firefly Optimization (HMF-IFO) algorithms. The explored HMF-IFO model to decrease PAPR and BER which were combined to address the problem in the MIMO-OFDM system. The main advantage of the explored HMF-IFO model was performed better in terms of power efficiency in transmitters and minimised the impact of non-linear distortions in the power amplifier and improved BER. However, the explored

HMF-IFO algorithms result in suboptimal PAPR and BER reduction due to the risk of local optima, especially multi-dimensional search spaces.

Nguyen [20] developed an efficient Convex Relation Method (CRM) based MIMO-OFDM for PAPR reduction without side information. The developed CRM with phase quantization technique was utilized for the estimation of phase factors in PTS. The main advantage of the developed CRM model was optimized transmission strategies that minimized Bit Error Rate (BER) and led to enhanced signal quality. However, the iterative nature of the CRM algorithm requires an extensive computational resource, which makes the developed CRM model inappropriate for certain conditions in PAPR reduction.

Ashish Goel and Saruti Gupta [21] designed a PAPR reduction model based on side information embedding scheme in OFDM system. The designed reduction model was employed to reduce the PAPR in OFDM system by reducing the optimal phase factor selection. An advantage of the designed model was that reduced computational complexity and enhanced the process also for higher order sub-blocks. However, the deigned PAPR reduction model based on side information scheme was sensitivity to error which was a significant drawback that led to degradation in BER performance.

Si-Yu Zhang and Hui Zheng [22] developed a hybrid model for PAPR reduction scheme in OFDM system based on phase rotation factors and dither signals. The developed PAPR reduction model was an integration of phase rotation factor and dither signals on sub-carriers in OFDM which was used to reduce the PAPR level. The main advantage of the developed hybrid model was utilization of partial sub-carriers that increased the BER performance. However, the developed hybrid model increased the computational complexity of the overall system.

The above-mentioned existing approaches have drawbacks in PAPR reduction such as suboptimal results in phase factor selection, slow convergence, and extensive computational resources. To overcome these limitations, an Inner Selection Learning strategy with a Chameleon Swarm Optimization algorithm (ISL-CSO) in the PTS scheme is proposed for effective PAPR reduction in the MIMO-OFDM system. The proposed ISL strategy improved the search for optimal set of phase factors which is employed in CSO algorithm led to reduce PAPR effectively. The ISL strategy learns and adapts the varying channel condition that helps to minimize PAPR and computational resources.

3. Methodology

The proposed PAPR reduction by PTS phase optimization in MIMO-OFDM includes mainly three phases: OFDM system model, PTS phase model and Proposed Optimization model. The block diagram for MIMO-OFDM is illustrated in Fig. 1. The detailed description of PAPR reduction is explained below.

3.1 MIMO-OFDM system model

The transmission of multiple inputs through transmitting and multiple outputs received by the receiving antenna in MIMO-OFDM is expressed as in Eq. (1):

$$B = \sqrt{\frac{e_s}{n_t n_o}} hs + \omega \tag{1}$$

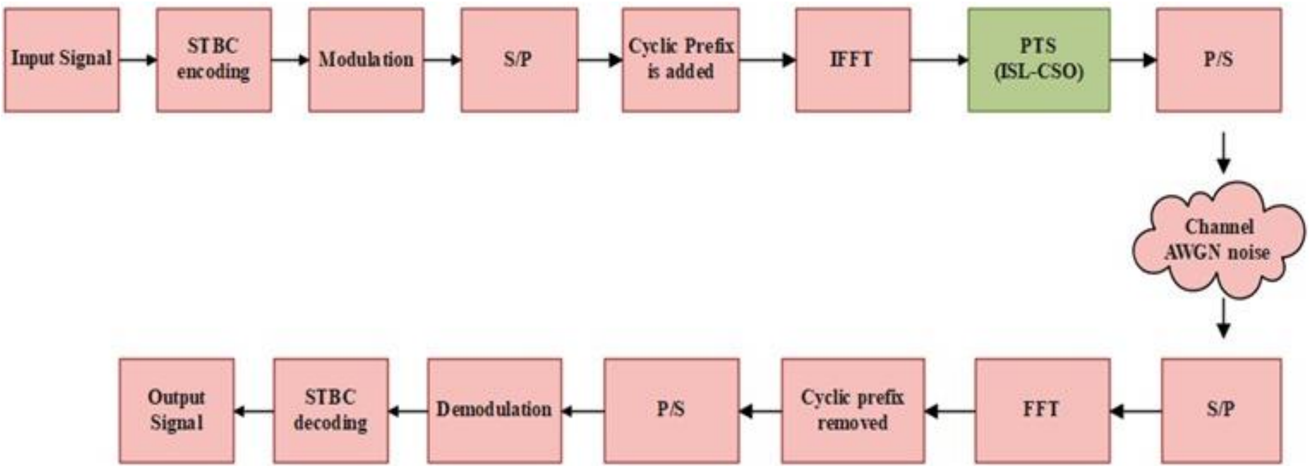

Figure. 1 Block Diagram of MIMO-OFDM

Where, n_t denotes transmitter antenna; n_o represents noise term; e_s indicates energy of the signal; h_s stands for channel matrix; ω refers to Additive Gaussian Noise (AWGN); B represents received signal matrix at the receiving antennas.

Initially, the bitstream is encoded into baseband-modified symbols using an STBC encoder, which are then divided into individual blocks. The signal from each block is then sent through a Serial-to-Parallel (S/P) converter and modulated by using QAM-16. An Inverse Fast Fourier Transform (IFFT) is applied to generate the OFDM signals. To alleviate inter-symbol and inter-carrier interference, a Cyclic Prefix (CP) is appended to each data block. The discrete-time signal is then passed through a Digital-to-Analog (D/A) converter, which converts it into an analogue signal, then amplified by a high-power amplifier for transmission [23].

At the receiver side, the Analog-to-Digital (A/D) converter converts the received signal back to digital form. Then Fast Fourier Transform (FFT) is then applied to recover original information and the cyclic prefix is removed. After that, the signals are fed into Parallel to Serial (P/S) converter and demodulated. Finally, the demodulated signals are decoded by an STBC decoder to reconstruct the transmitted information. The mathematical representation of discrete-time in OFDM signal is expressed in Eq. (2).

$$x_k = x(k.T/L) = \frac{1}{\sqrt{N}} \sum_{n=1}^{N-1} X_n e^{i2\pi nk/NL}, k = 0,1,\dots,NL-1 \quad (2)$$

Where, x_k represents discrete-time OFDM signal; T and L denotes sampling period and oversampled factor, $\frac{1}{\sqrt{N}}$ normalization factor, $L \geq 4$ is generally appropriate to determine peak signals; $X_n$refers to complex data symbol modulated for the n^{th}subcarrier, $e^{i2\pi nk/NL}$represents basic function of Fourier transform, i denotes imaginary unit, $x = [x_0, x_1, \dots, x_{NL-1}]^T$ indicates oversampling time-domain signal.

3.1.1. PAPR and HPA

The multiple sub-carriers with nearby phases lead to high PAPR by overlapping and results while amplifying the distortion in a non-linear region of HPA. This signal distortion reduces degradation of BER. The PAPR in the OFDM signal is represented in Eq. (3):

$$PAPR\ (x) = 10 \log \frac{\max |x|^2}{E\ [|x|^2]}\ (dB) \quad (3)$$

Where, $PAPR\ (x)$ represents the peak to average power ratio of signal x, max $|x|^2$ denotes maximum power, $E\ [|x|^2]$ indicates expected value (mean).

The Complementary Cumulative Distribution Function (CCDF) is most widely utilized as a technical indicator in MIMO-OFDM systems. This CCDF metric is used to accurately depict the dispersion of regular PAPR level which is said to refers to the probability that PAPR of an OFDM symbol exceeds a specified threshold Z_0 . Mathematical representation of CCDF is expressed as in Eq. (4);

$$P_r(PAPR > Z_0) = 1 - (1 - e^{-z_0})^{LN} \quad (4)$$

Where, z_0 represents threshold value; N denotes subcarriers. However, the model concentrates on amplitude nonlinearity due to less contribution of phase for OFDM signal in signal distortions.

3.2 Partial Transmit Sequence (PTS)

The PTS method reduces the PAPR in OFDM efficiently without any signal distortion of signals, which is suitable for 5G high-order M-QAM scenarios. The principle of the PTS method is to find appropriate phase factors in the time domain to various phase concentrations of sub-carrier and decrease PAPR level in OFDM signal. The process of the PTS method is described as follows:

- Initially, the signals are transformed into frequency and time domain segmentation.
- Generating a scrambling sequence that involves full and finite sampling space arbitrarily.
- The selection of dynamically generated sequence of symbols according to minimum PAPR from sampling space in time domain by finding deeply in a determined sampling space.

The input data x is divided into disjoint sub-locks $X_v = \left[X_{v,0}, X_{v,1}, \dots, X_v, N-1\right]^T$, $v = 1,2,\dots,V$. The orthogonal partition in PTS is expressed as in Eq. (5) and Eq. (6):

$$X = \sum_{v=1}^{V} X_v \quad (5)$$

$$s.t \begin{cases} x\ (X_i) \cap x\ (X_j) = \phi & i \neq j \quad i,j = 1,2,\dots,V \\ x\ (X_i) \cap x\ (X_j) = x\ (X_i) & i = j \quad i,j = 1,2,\dots,V \end{cases} \quad (6)$$

Where, $x(V)$ represents support vector V. The position of each subcarrier which are presented in the other block is zero, hence the integration of all sub-blocks (X_v) establishes actual signal. The partition of sub-blocks is categorized into three types of Interleaved, Pseudo-random and Adjacent partitions respectively. The PAPR reduction mainly depends on sub-block partitioning in PTS. To measure the effect of PAPR, autocorrelation function and PTS play a vital role which is mathematically formulated as in the given Eq. (7):

$$R(\tau)_{Pr} = \begin{cases} \frac{1}{V}\left|\sum_{v=0}^{V-1} b_v^i b_v^{j*}\right| & \tau = 0 \\ 0 & \tau \neq 0 \end{cases} \quad (7)$$

Where, $\tau = 0,1,\ldots,N-1$, $v = 1,2,\ldots,V$; $\tau \neq 0$ denotes an autocorrelation function of pseudo-random partition which is small and results in the finest PAPR reduction. The group of phase factors is formulated in a scramble sequence which is represented in Eq. (8):

$$b = [b_1, b_2, \ldots, b_v]^T \quad (8)$$

Where, the complex rotation factors $b_v = e^{i\phi_v}, \phi_v \epsilon\, [0, 2\pi]$ is presented domain to scramble and sparse sub-carrier concentration to reduce PAPR. After scrambling and combining time domain signal in OFDM is represented in Eq. (9):

$$x'(b) = \sum_{v=1}^{V} b_v . x_v = \sum_{v=1}^{V} b_v . IFFT(X_v) \quad (9)$$

Where, $x'(b) = [x'_0(b), x'_1(b), \ldots, x'_{NL-1}(b)]^T$. The set of allowed phase factors is given in Eq. (10):

$$\Theta = \left\{e^{i2\pi l/W} \,\middle|\, l = 0,1,\ldots,W-1\right\}, \;\; b_v \epsilon \Theta \quad (10)$$

Where, W stands for number of allowed phase factor; Θ and consists possibility of W various values. The candidate rotation phase matrix with W^v dimension is expressed in Eq. (11):

$$\beta = \begin{bmatrix} b_{1,1,} & b_{1,2,} & \cdots & b_{1,W^v} \\ \vdots & \vdots & \cdots & \vdots \\ b_{V,1} & b_{V,1} & \cdots & b_{V,,W^v} \end{bmatrix}_{V \times, W^v} \quad (11)$$

To find and locate an appropriate scrambling sequence from full space β is especially difficult because of constraints of computational complexity. However, there are some issues while reducing PAPR reduction such as sub-optimal phase factor selection, side information and latency. These problems lead to poor power efficiency and increased distortion that results in signals with high PAPR than necessary. To address these limitations, an ISL-CSO algorithm is proposed for PAPR reduction with the PTS technique in the MIMO-OFDM system.

3.3 Proposed Inner Selection Learning-Chameleon Swarm Optimization

The chameleons are present in all areas that explore several regions and utilize the spherical eyes to search area for finding the prey. After finding the prey, the chameleons use their long and sticky tongues to catch the prey quickly. The CSA is a population-based algorithm which is initialized by a population of n chameleons searching in a d-dimensional hyperspace [24]. Fig. 2 illustrates the workflow of the proposed ISL-CSO in the PTS scheme.

The phase factors of PTS are represented as complex numbers (or angles) and belong to a set of predefined values, such as $\{+1, \pm j\}$, where j is the imaginary unit, or more generalized values from a set of quantized phases like $\{0, \pi/2, \pi, 3\pi/2\}$. These factor values are related to the initialization parameters of the CSO algorithm. The chameleon population is defined as $n \times d$ dimensional 2D y-matrix which is expressed in Eq. (12):

$$y_t^i = [y_{t,1}^i, y_{t.2}^i, \ldots, y_{t,d}^i] \quad (12)$$

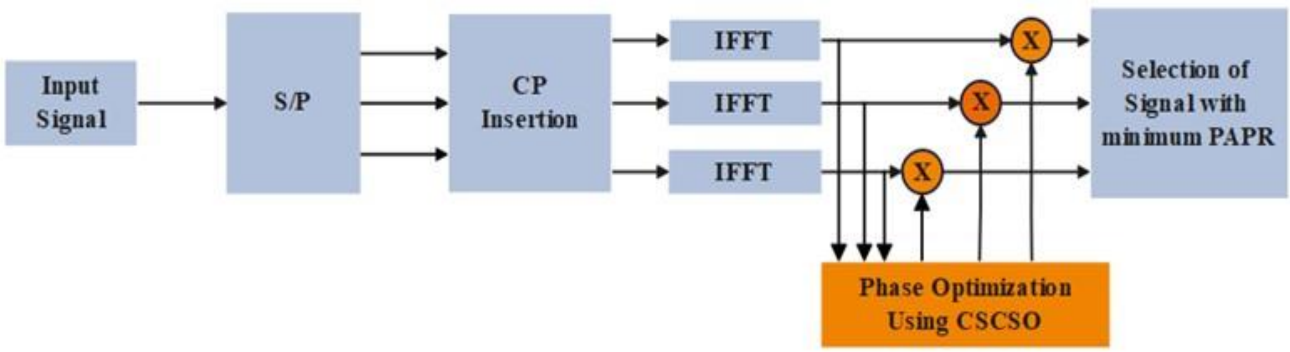

Figure. 2 Workflow of proposed IS-CSO algorithm in MIMO-OFDM.

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Where $i = -1,2,3,\dots,n$ and t denotes valid iterations; $y_{t,d}^{i}$ indicates position of chameleons in d th dimension. The initial positions of every chameleon are generated by the Eq. (13):

$$x_{i,j}^{t=0} = lb_j + r_1 \times \left(ub_j - lb_j\right) \quad (13)$$

Where, $x_{i,j}^{t=0}$ represents initial position of i th chameleon; r_1 denotes uniformly generated random number; ub_j and lb_j indicates upper and lower limits of allowable search space in each dimension j. After the initial positions of the chameleons have been established the CSA then performs a fitness evaluation. The optimization process is performed based on the fitness functions are categorized into three sub-phases as Searching Prey, Rotation of Eyes and Hunting Prey.

3.3.1. Fitness function

After the initialization and random generation of chameleons, the fitness of each chameleon is estimated at every iteration. The fitness function of CSO is related to PAPR value. Based on this PAPR value, the optimal phase factor is identified and selected for the PAPR reduction process. The fitness value is mathematically formulated as in Eq. (14) and Eq. (15):

$$fitness\ function\ (X)^j = \begin{cases} x \le x_c \\ x \ge x_g \end{cases} \quad (14)$$

$$(X)_{fitness}^{j} = \{\min P_{err}; \max x_{optimum} \quad (15)$$

Where, x_c and x_g denotes threshold value that satisfies the predefined elements of P_c and P_g.

3.3.2. Searching prey

While searching for food, the chameleon changes position and body color depending on the nature of the environment. These changes in chameleon position are achieved by the position update Eq. (16):

$$y_{t+1}^{i,j} = \begin{cases} y_{i,j}^{t} + p_1\left(P_t^{i,j} - G_t^{i,j}\right)r_2 + p_2\left(G_t^{i,j} - y_t^{i,j}\right)r_1 & if r_1 \ge P_p \\ y_{i,j}^{t} + \mu\left(\left(u_j - l_j\right)r_3 + l_b^{j}\right) sgn\ (rand - 0.5) & if r_i < P_p \end{cases} \quad (16)$$

where $y_{i,j}^{t+1}$, denotes new position of i^{th} chameleon; $y_{i,j}^{t}$ represents current position of chameleon. $P_t^{i,j}$ indicates personal best position of j^{th} size chameleon in t^{th} iteration loop; $G_t^{i,j}$ indicates global best position in j^{th} dimension attained by any chameleon in t^{th}iteration. p_1 and p_2, stands for acceleration coefficients that control exploration ability; r_1, r_2 and r_3, denotes random numbers; r_i represents random number which are generated ubiformly in an index i ; P_p , denotes probability threshold; $sgn\ (rand - 0.5)$ refers to sign function provide +1 or -1 according to ransom number; μ represents scaling factor. u_j and l_j stands for upper and lower bounds of search space.

3.3.3. Rotation of eyes

The independent movement of a chameleon's eyes is prepared to search with the ability of rotating eyes to spot any prey over 360◦. Chameleons locate the prey by using their spherical eyes, which can rotate independently. By using this information, the chameleons geometrically move to a new position which is mathematically expressed and summarized step by step. Initially, the chameleon location is converted to centre, that means to origin, then a rotation matrix is determined, and position is updated corresponding for defining the matrix. At last, the chameleon returned to its actual position.

3.3.4. Hunting of prey

The chameleon captures the prey by using its clingy tongue when approaching the prey. This process is implemented mathematically as shown in Eq. (17):

$$v_{t+1}^{i,j} = \omega v_{i,j}^{t} + c_1\left(G_t^{i,j} - y_t^{i,j}\right)r_1 + c_2\left(P_t^{i,j} - y_t^{i,j}\right)r_2 \quad (17)$$

where $v_{t+1}^{i,j}$ represents new speed of chameleon in j. In iteration, size $t+1$ represents present speed of $v_{i,j}^{t}$ j; $\omega v_{i,j}^{t}$ indicates present location of the chameleon in t th dimension. $P_t^{i,j}$ and $G_t^{i,j}$ denotes best-known position and global position of chameleons, c_1 and c_2 indicates constants that control effect of $P_t^{i,j}$ and $G_t^{i,j}$ falls while the chameleon's tongue, r1 and r2 are random numbers, and ω indicates inertia weight.

3.3.5. Inner selection learning

Most of the optimization algorithms utilize the Opposition-Based Learning (OBL) strategy to improve exploration (searching) of solution by using reverse solving, therefore it leads to an optimal solution. However, this OBL has certain drawbacks such as an imbalance between local and global search ability of algorithm, and can adapt to dynamic environment. Also, the algorithm has certain limitations that trap in local optima and diversity is minimized which results in premature convergence. To overcome these drawbacks, an inner selection learning mechanism is introduced with the CSA to update optimal position. A two arbitrarily selected individuals are connected to optimal position then inner position is estimated by an inner principle of the triangle, when a discrete group of points in D-dimensional space follows a triple point, inner heart of these points is defined as I_d, then inverse point x^* of x is given in Eq. (18):

$$x^* = 2.I_d - x \tag{18}$$

The main advantage of the integrated inner reversal point which is created from the locations not from the population that makes CSO model to preserve internal information of an actual population as well as balanced the local and global search. An optimal position update has a crucial guiding role, which is updated in a various and complex way. This requires a large range of exploration in an initial phase, balance between exploration and exploitation in middle stage, and to increase local exploitation ability in future phase, to identify a better and high-quality feasible solution. Finally, the integration of the ISL strategy with the CSO metaheuristic optimization algorithm enhanced the PAPR reduction with the PTS technique in the MIMO-OFDM system.

4. Results and discussion

The experimental results of proposed ISL-CSO algorithm-based PAPR reduction in the MIMO-OFDM system are illustrated in this section. The proposed method is simulated on MATLAB R2021b version 9.11 with a system configuration of an i5 processor and 6GB RAM. The evaluation of proposed algorithm is estimated by three performance metrics Bit Error Rate (BER), Symbol Error Rate (SER), and Complementary Cumulative Distribution Function (CCDF). The performance analysis of proposed ISL-CSO algorithm is evaluated with past optimization methods utilized in PTS such as Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO), Ant Colony Optimization (ACO) and CSO algorithms respectively. Table 1 illustrates the parameter settings of the proposed ISL-CSO algorithm for PAPR reduction.

Table 1. Parameters results of the proposed method

Parameters	Value
Subcarrier numbers of OFDM	1024
Transmit antenna numbers	4
Receiver antenna numbers	2
Modulation	16-QAM
Bandwidth of the system	20 MHz
Iteration numbers	50
AWGN variance	0.01
Size of FFT	6
Frequency of the carrier signal	4000 Hz

4.1 Qualitative and quantitative analysis

The quantitative and qualitative analysis of the proposed ISL-CSO model in the PTS scheme employed for PAPR reduction which are estimated by various performance metrics that are illustrated in Fig. 3 to Fig. 6. The performance metrics utilized for evaluation of the proposed ISL-CSO algorithm are BER, SER and CCDF. The proposed 16-QAM modulation and ISL-CSO algorithm is evaluated with existing modulation techniques and optimization algorithms which are used for PAPR reduction. The proposed method is evaluated with existing optimization methods such as ACO, GWO, and CSO. The modulation technique utilized in this research 16-QAM is evaluated with the other modulation techniques like Frequency Shift Keying (FSK), Quadrature Phase Shift Keying (QPSK) and QAM. Fig. 3 and Fig. 4 represent performance of proposed ISL-CSO algorithm and the 16-QAM modulation in BER which attained better results than existing approaches. From Fig. 3, it is clear that the proposed ISL-CSO method attained less BER than other existing PAPR reduction techniques.

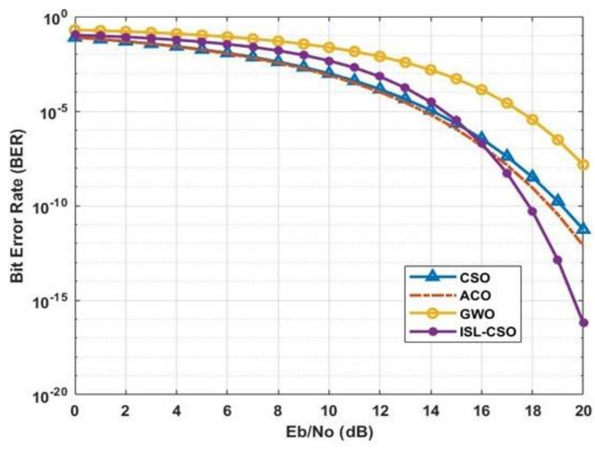

Figure. 3 Performance analysis of ISL-CSO in BER

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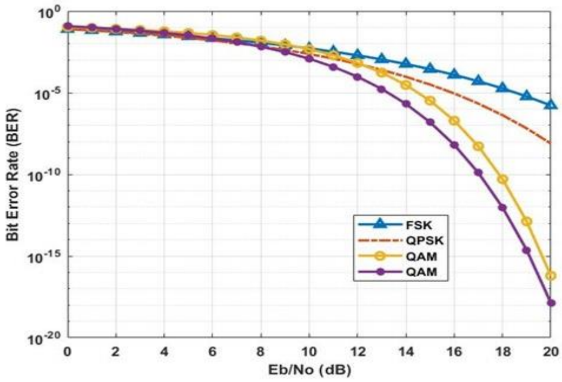

Figure. 4 Performance analysis of QAM in BER

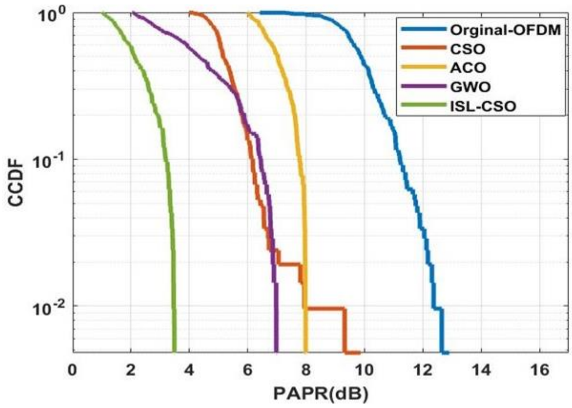

Figure. 5 Performance analysis of ISL-CSO in PAPR

The proposed method ISL-CSO is estimated with original OFDM, ACO, GWO, and CSO, similarly the 16-QAM modulation is also evaluated with Original OFDM, FSK, QPSK and QAM. Fig. 5 and Fig. 6 illustrate the performance analysis of ISL-CSO and modulation technique QAM in CCDF.

From Fig. 5, the proposed ISL-CSO algorithm achieved better results which dynamically selects best best-performing phase factor during each iteration based on the fitness value. This strategy prevents inefficient solutions selected by the CSO optimization algorithm and ensures only that the best phase factors contribute to reducing PAPR in MIMO-OFDM.

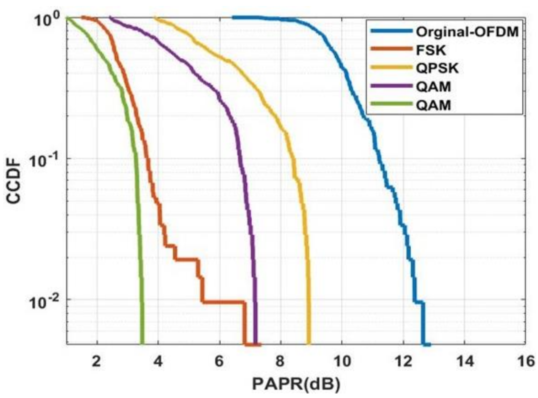

Figure. 6 Performance analysis of QAM in PAPR

4.2 Comparative analysis

The comparative analysis of proposed ISL-CSO algorithm is evaluated with existing PTS optimization methods with different scenarios and is depicted in Tables 2 and 4. The performance metrics used for comparative analysis are BER and CCDF. Tables 2 and 3 represent the Scenario and comparative analysis of ACO [16] respectively.

The comparative analysis of the proposed ISL-CSO algorithm is evaluated with existing PTS optimization methods. The performance metrics used for comparative analysis are BER and CCDF. Tables 4 and 5 represents Scenario and comparative analysis of MDO [17] respectively.

The comparative analysis of the proposed ISL-CSO algorithm is evaluated with existing PTS optimization methods. The performance metrics used for comparative analysis are BER, and CCDF. Tables 6 and 7 represent Scenario and comparative analysis of OOA [18] respectively.

Table 2. Scenario of ACO [16]

Parameters	Scenario 1 ACO [16]
No. of Subcarriers	64
Modulation	Offset QAM
Channel	AWGN

Table 3. Comparative Analysis of Proposed method for BER with respect to CCDF=10^{-2}

Author	Method	BER
Kumar [16]	ACO	7.2×10^{-2}
Proposed Method	ISL-CSO	4.3×10^{-2}

Table 4. Scenario of MDO [17]

Parameters	Scenario 2 MDO [17]
No. of Subcarriers	1024
Modulation	QPSK
Channel	Gaussian

Table 5. Comparative Analysis of BER of Proposed method with respect to CCDF=10^{-2}

Author	Method	BER
Jothi and Chandrasekar [17]	MDO	6.8×10^{-2}
Proposed Method	ISL-CSO	3.6×10^{-2}

Table 6. Scenario of OOA [18]

Parameters	Scenario 3 OOA [18]
Modulation	16-QAM
Channel	Rayleigh Fading

Table 7. Comparative Analysis of PAPR value in (dB) of Proposed method based on iterations

Methods	PAPR (dB)				
	2	4	6	8	10
OOA [18]	34	50	69	88	93
Proposed ISL- CSO	26	38	49	72	84

Table 8. Comparative Analysis of computational complexity of Proposed method based on input size

Methods	Input size				
	200	**400**	**600**	**800**	**1000**
OOA [18]	300	750	1200	1970	2170
Proposed ISL-CSO	285	720	1190	1860	2150

Table 9. Scenario of Side information embedding scheme [21]

Parameters	**Scenario 2** Side information embedding scheme **[21]**
No. of Subcarriers	64,128 and 256
Modulation	QPSK
Channel	AWGN

Table 10. Comparative Analysis of BER of Proposed method with respect to CCDF=10^{-3}

Author	**Method**	**PAPR**
Ashish Goel and Saruti Gupta [21]	Side information embedding scheme	9.2
Proposed Method	ISL-CSO	8.5

Table 11. Scenario of phase rotation factors and dither signals [22]

Parameters	**Scenario 2** Side information embedding scheme **[21]**
No. of Subcarriers	128
Modulation	QPSK

Table 12. Comparative Analysis of BER of Proposed method with respect to CCDF=10^{-2}

Author	**Method**	**PAPR**
Si-Yu Zhang and Hui Zheng [22]	Phase rotation factors and dither signals	5.8
Proposed Method	ISL-CSO	4.2

The computational complexity of proposed ISL-CSO method is evaluated with OOA [18] method is represented in Table 8. It is clear that, the computational complexity of the proposed method is less than that the existing approach which select optimal phase factor in a less iteration with the help of inner selection strategy.

The comparative analysis of the proposed ISL-CSO algorithm is evaluated with existing PTS optimization methods. The performance metrics used for comparative analysis are PAPR and CCDF. Tables 9 and 10 represents Scenario and comparative analysis of Side information embedding scheme [21] respectively.

The comparative analysis of the proposed ISL-CSO algorithm is evaluated with existing PTS optimization methods. The performance metrics used for comparative analysis are PAPR and CCDF. Tables 11 and 12 represents Scenario and comparative analysis of phase rotation factors and dither signals [22] respectively.

4.3 Discussion

The Proposed ISL-CSO algorithm achieved better results in PAPR reduction utilized with the PTS Scheme in the MIMO-OFDM scheme. However, the existing approaches have drawbacks in PAPR reduction such as the ACO [16] model has a slow convergence rate that affects the processing speed of the communication system. The iterative nature of the MDO [17] algorithm requires an extensive computational resource, which makes the developed MDOC model inappropriate for certain conditions in PAPR reduction. The integration of OOA [18] for PAPR reduction in OFDM systems requires additional implementation efforts, especially in terms of algorithm design and adaptation which increases the complexity of communication systems. To overcome these limitations, an ISL-CSO is proposed for the PAPR reduction MIMO-OFDM system. The ISL-CSO optimization searches and selects optimal phase factors and reduces the PAPR which is crucial for maintaining the quality of transmitted signals, this strategy enhances overall communication efficiency by optimizing power efficiency without signal distortion. The proposed CSO optimization algorithm reduced the requirement of an extensive search by focusing on optimal phase factor sets leading to minimising both PAPR and CCDF levels in MIMO-OFDM.

5. Conclusion

An Inner Selection Learning strategy (ISL) is employed with the Chameleon Swarm Optimization (CSO) algorithm for PAPR reduction in OFDM. The proposed ISL-CSO balances the exploration and exploitation of phase factors efficiently and reduces the occurrence of high PAPR values that result in lower CCDF. The PAPR reduction by ISL-CSO also ensures that signals are within the amplifier's linear range which reduces the risk of maintaining better signal quality and avoiding signal distortion. Initially, the system model of OFDM is designed based on 16-QAM modulation and the STBC is utilized for encoding/decoding of the signals. The PTS in OFDM is often used for PAPR reduction by optimizing the phase factor correctly. Thus, the proposed ISL-CSO algorithm is used to select the optimal phase factors and also reduce the PAPR in the OFDM system effectively. The experimental results show that the proposed method achieved BER of 4.3×10^{-2} and PAPR of 2 dB for 26 iterations which is less than the existing approaches such as ACO and OOA. In future, a hybrid metaheuristic optimization algorithm will be implemented to enhance PAPR reduction in MIMO-OFDM.

Notation

Notation	Description
n_t	Transmitter antenna
n_o	Noise term
e_s	Energy of the signal s
h_s	Channel matrix
ω	Additive Gaussian Noise (AWGN)
B	Received signal matrix at the receiving antennas
x_k	Discrete-time OFDM signal
T and L	Sampling period and oversampled factor
$\frac{1}{\sqrt{N}}$	Normalization factor
$L \geq 4$	To determine peak signals
X_n,	Complex data symbol modulated for the n^{th}subcarrier
$e^{i2\pi nk/NL}$	Basic function of Fourier transform
i	Imaginary unit
$x = [x_0, x_1, \dots, x_{NL-}$	Oversampling time-domain signal
$PAPR\ (x)$	The peak to average power ratio of signal x
$\max \lvert x\rvert^2$	Maximum power
$E\ [\lvert x\rvert^2]$	Expected value (mean)
z_0	Threshold value
N	Subcarriers
$x(V)$	Support vector V
$\tau \neq 0$	Autocorrelation function of pseudo-random partition
W	Number of allowed phase factor Θ
β	Full space
t	Valid iterations;
$y_{t,d}^{i}$	Position of chameleons in d th dimension
$x_{i,j}^{t=0}$	Initial position of ith chameleon;
r_1	Uniformly generated random number;
ub_j and lb_j	Upper and lower limits of allowable search space in each dimension j
x_c and x_g	Threshold value that satisfies the predefined elements of P_c and P_g
$y_{i,j}^{t+1}$	New position of i^{th} chameleon;
$y_{i,j}^{t}$.	Current position of chameleon.
$P_t^{i,j}$	Best position ever taken by the j^{th} size chameleon in the t^{th} iteration loop;
$G_t^{i,j}$	Global best position in j^{th} dimension achieved by any chameleon in t^{th}iteration
p_1 and p_2	Two positive numbers that control exploration ability;
r_1, r_2 and r_3	random numbers
r_i	uniformly generated random number in the index i
P_p	chameleon's probability of detecting prey
$sgn\ (rand - 0.5)$	an effect on the exploration direction;
μ	parameter defined as a function of decreasing iterations
$v_{t+1}^{i,j}$	new speed of chameleon in j. In iteration,
size $t+1$	the current speed of $v_{i,j}^{t}$j
$\omega v_{i,j}^{t}$	the current position of the chameleon in t th dimension.
$P_t^{i,j}$ and $G_t^{i,j}$	current chameleon's best-known position and best global position ever known to chameleons,
c_1 and c_2	two positive constants controlling effect of $P_t^{i,j}$and $G_t^{i,j}$ falls while the chameleon's tongue
r1 and r2	random numbers, distributed in the range 0 to 1
ω	inertia weight
I_d then the inverse point x^* of x	triple point whose inner heart

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

The paper conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation, writing—review and editing, visualization, have been done by 1st and 3rd author. The supervision and project administration, have been done by 2nd author.

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