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Enhancing PAPR reduction efficiency in MIMO-OFDM systems via selective mapping and metaheuristic algorithms

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ABSTRACT

The relentless evolution of communication systems, driven by the demands of 5G and the impending 6G networks, necessitates heightened data rates and spectral efficiency. orthogonal frequency division multiplexing (OFDM), a form of multicarrier modulation employed in multi-input multi-output (MIMO) systems, stands as a pivotal technology. Yet, OFDM grapples with challenges, notably the peak-to-average power ratio (PAPR) issue. Selective mapping (SLM) has been a favored technique for mitigating PAPR in OFDM, albeit challenged by computational complexities in its pursuit of discovering optimal phase factors. This paper pioneers a transformative approach by integrating metaheuristic algorithms genetic algorithm (GA), particle swarm optimization (PSO), and the innovative fireworks algorithm (FWA) into SLM for PAPR reduction while minimizing computational complexity. Simulation results not only affirm the efficacy of SLM-based techniques but also spotlight the potential of metaheuristic algorithms in addressing PAPR challenges in modern communication systems. The study transcends single-antenna systems, extending to MIMO-OFDM systems based on WiMAX standards, validating the efficacy of these techniques in multi-antenna configurations. Crucially, the FWA, proposed for the first time in this paper, emerges as a robust candidate, striking an enviable balance between computational efficiency and performance, achieving a notable PAPR reduction with a favorable search number.

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1. INTRODUCTION

Multicarrier modulation (MCM) is pivotal in advancing wireless communication across 4G, 5G, and upcoming 6G networks. Techniques like orthogonal frequency division multiplexing (OFDM), filter bank multicarrier (FBMC), generalized frequency division multiplexing (GFDM), and universal filtered multicarrier (UFMC) provide spectral efficiency, channel robustness, and flexibility [1]–[4]. In 4G, especially long-term evolution (LTE), OFDM is the primary scheme [5], enabling simultaneous data transmission on orthogonal subcarriers, optimizing spectrum use, and enhancing capacity. Its resilience to fading channels and compatibility with technologies like multi-input multi-output (MIMO) contribute to high data rates and system performance. As 5G emerges, MCM techniques, particularly OFDM, remain fundamental [6]. The 3GPP's selection of OFDM in 5G's NR air interface underscores its advantages and proven track record in previous wireless technologies [4], facilitating integration with technologies like massive MIMO.

Despite the notable advantages of OFDM systems, a pronounced challenge arises from the significant variation in the transmitted signal's envelope, commonly denoted as the peak-to-average power ratio (PAPR). This variation not only compromises the efficiency of high-power amplifiers (HPA) but also introduces complexities in nonlinear components, leading to out-of-band radiation and subsequent degradation in the bit error rate (BER). To address this challenge, various approaches have been proposed to mitigate high PAPR in both OFDM [6]–[9] and MIMO-OFDM signals [10]–[12]. These approaches encompass techniques such as clipping [13], clipping and filtering [14], tone injection [15], coding [16], peak windowing [17], selected mapping (SLM) [18], [19], and partial transmit sequence (PTS) [20]–[22].

The SLM technique stands out as a widely adopted approach in OFDM systems for effectively mitigating the PAPR of transmitted signals. Its core concept involves generating multiple versions of the original OFDM signal by applying distinct phase sequences, referred to as phase candidates, to the data symbols. These carefully chosen phase candidates serve the purpose of minimizing the PAPR of the composite signal, offering a significant advantage in avoiding substantial bandwidth or power penalties associated with PAPR reduction techniques.

However, the notable effectiveness of the SLM technique comes at the expense of increased computational complexity. The process of generating and evaluating phase candidates introduces additional intricacy, posing challenges to the feasibility of implementation. This heightened complexity raises considerations regarding the practical implementation of the SLM technique and its impact on computational requirements. To pave the way for novel advancements in mitigating the PAPR challenges of OFDM systems, this paper introduces a groundbreaking approach. Here, we propose the pioneering application of the fireworks algorithm (FWA) [23], [24] within the framework of the SLM method. This innovative integration of FWA aims to address the computational complexities associated with SLM and significantly reduce the PAPR. In addition to FWA, we leverage other state-of-the-art swarm intelligence algorithms, such as genetic algorithms (GA) [25], [26] and particle swarm optimization (PSO) [27], [28]. These metaheuristic algorithms collectively contribute to the reduction of computational complexity while ensuring the preservation of PAPR performance. By introducing FWA to the SLM method, we embark on a novel exploration in the realm of PAPR reduction, marking a significant contribution to the existing body of knowledge. The remainder of this paper unfolds as follows: In section 2, we introduce the MIMO-OFDM system model, illuminate the PAPR problem, and expound on the foundational principles of SLM techniques. Section 3, titled "Method," delves into the intricacies and algorithmic details of our innovative approach integrating SLM with the intelligent swarm optimization algorithm of fireworks. moving forward, section 4 conducts an in-depth performance evaluation through extensive simulations and comparative analyses, shedding light on the effectiveness of the proposed swarm intelligence-based solution. Finally, in section 5, we encapsulate the study with a concise yet comprehensive conclusion, summarizing key findings and outlining potential avenues for future research.

2. MIMO-OFDM SYSTEM AND SLM METHOD

2.1. PAPR of the MIMO-OFDM signal

The integration of MIMO technology with OFDM represents a powerful approach in modern wireless communication systems. MIMO-OFDM systems can achieve high data rates, improved link reliability, and increased spectral efficiency. By utilizing multiple antennas, MIMO technology enables spatial multiplexing, facilitating parallel data stream transmission. Generally, space-time block code (STBC) is specifically employed for MIMO configurations with two, three, or four antennas [29]–[31]. In the case of MIMO-OFDM with two transmitting antennas, it is common to employ the Alamouti code. The encoder signal, employing the Alamouti code, takes the input signal X = [X(0), X(1), …, X(N-1)] and generates two output signals X_1 and X_2 to be transmitted simultaneously from the two antennas.

$$\begin{aligned} X_1 &= [X(0), -X^*(1), \dots, X(N-2), -X^*(N-1)]^T \\ X_2 &= [X(1),\ X^*(0), \dots, X(N-1), X^*(N-2)]^T \end{aligned} \tag{1}$$

Antennas 1 and 2 transmit the signals X_1 and X_2, respectively.

In MIMO-OFDM systems with N_T transmitted antennas, the expression below quantifies the peak power fluctuation:

$$PAPR_{MIMO-OFDM} = \max\{PAPR(x_i)\}, \qquad i = 1, \dots, N_T \tag{2}$$

where the time domain signal (x_i) at each transmit antenna is represented by [32].

$$x_i[n] = \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} X_k^i e^{\frac{j2\pi nk}{LN}} \quad (3)$$

In this context, N represents the number of subcarriers, L is the oversampling factor (L=4), While X_k denotes the n^{th} complex symbol transported and propagated through the k^{th} subcarrier. The PAPR at each antenna of a MIMO-OFDM system is defined as [32]:

$$PAPR(x_i) = \frac{max\{|x_i[n]|^2\}}{E\{|x_i[n]|^2\}}, \quad 0 \leq n \leq NL-1, \quad (4)$$

with $x_i[n]$ calculated using (3) and E{.} representing the average power across all time instances.

2.2. PAPR reduction by selected mapping technique

The selected mapping technique is widely recognized as a highly effective means of reducing PAPR in both SISO-OFDM and MIMO-OFDM systems. It was initially proposed by Muller and Huber [33], [34] and further detailed by Breiling *et al.* [35]. By utilizing multiple versions of the same signal, SLM involves phase rotations through multiplication. One version of the complex symbol sequence resulting from digital modulation is multiplied by a phase vector, and the version with the lowest PAPR is selected for transmission after the IFFT operation. Figure 1 illustrates the OFDM modulation process using this method.

Let $X = \{X_k\} = [X_0, X_1, ..., X_{N-1}]^T$ be the vector of OFDM symbols in the frequency domain. Here, N represents the overall number of subcarriers. The fundamental idea behind the SLM technique is to multiply the vector X by a vector $\varphi^{(u)} = \{\varphi_k^{(u)}\} = [\varphi_0^{(u)}, \varphi_1^{(u)}, ... \varphi_{N-1}^{(u)}]^T$, where the elements $\varphi_k^{(u)}$ are in the form $\varphi_k^{(u)} = e^{j\varphi_k^{(u)}}$, with $\varphi_k^{(u)} \epsilon [0,2\pi)$ for $k = 0,1,...,N-1$ and $u = 1,2,...,U$. After the weighting (i.e., phase rotation), U different versions of the N components of the original OFDM signal are obtained, and the new OFDM signal in the frequency domain can be expressed as (5).

$$X^{(u)} = X \cdot \varphi^{(u)} = [X_0^{(u)}, X_1^{(u)}, ... X_{N-1}^{(u)}]^T \quad (5)$$

Finally, the temporal sequence of the OFDM signal marked by index u, which has the lowest PAPR and is selected for transmission, can be expressed as (6).

$$x^{(u^*)} = IDFT(X^{(u^*)}) \quad (6)$$

Where $u^{(*)}$ represents the index corresponding to the OFDM signal with the lowest PAPR. For proper reconstruction of the initial signal, the value of the index $u^{(*)}$ must be transmitted to the receiver using an error correction code. Several works have been proposed in the literature to address this issue of information sequence transmission [36], [37].

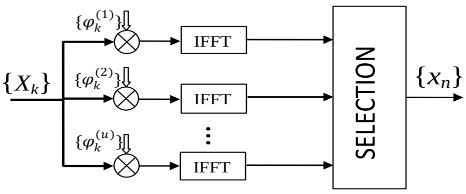


Figure 1. Block diagram illustrating the principle of the SLM technique for PAPR reduction

The SLM technique has been extensively researched and proven to be an effective method for PAPR reduction. However, the implementation of the SLM technique introduces additional complexity in terms of generating and evaluating phase candidates. This increased complexity can have implications for the feasibility of implementation and the computational requirements of the system. Therefore, it is important to carefully assess the trade-offs between the potential benefits of PAPR reduction and the increased complexity associated with implementing the SLM technique. In this paper, we propose the utilization of metaheuristic algorithms to mitigate the computational complexity. Specifically, we introduce the use of innovative swarm intelligence algorithms such as the FWA, which has shown promise in efficiently addressing complex optimization problems. By leveraging these algorithms, we aim to reduce the computational requirements and enhance the effectiveness of the SLM technique for PAPR reduction.

3. METHOD

Swarm intelligence is a prominent field in computational intelligence, exploring decentralized, self-organized systems with simple agents that exhibit complex global behavior, inspired by natural phenomena like bird flocking and ant foraging. Swarm intelligence algorithms, such as PSO [27], [28], [38], ant colony optimization (ACO) [39], and GA [25], have been developed to solve optimization problems [26], [40]. Additionally, the FWA, designed with fireworks explosions as a source of inspiration, has gained attention in the SI community. Research efforts focus on algorithm design, optimization, problem solving, and the application of swarm intelligence to tackle large-scale problems involving big data. The cooperative nature of these algorithms holds the potential to overcome optimization challenges and drive further research in real-world problem-solving. In the upcoming sections, we will comprehensively present the fundamental principles, implementation details, and performance evaluation of the FWA integrated with SLM. Our objective is to systematically and thoroughly elucidate the combination of FWA and SLM, providing insights into their cooperative mechanisms. This section serves as a comprehensive guide to the methodologies employed in our research, focusing on the integration of the optimization algorithm with the SLM technique for PAPR reduction with minimal complexity. We commence by elucidating the fundamental principles behind FWA and SLM, outlining their individual contributions to mitigating high PAPR in OFDM signals. Subsequently, we present a step-by-step algorithmic description of our novel approach, encompassing the most important theoretical formulas and simulation procedures.

3.1. PAPR reduction with fireworks algorithm based SLM in OFDM

In this sub-section, we present a novel approach that integrates the FWA with SLM to tackle the challenge of reducing the PAPR in OFDM systems. Our objective is to identify the most suitable combination of phase vectors that achieves significant PAPR reduction while ensuring computational efficiency. The FWA, similar to other swarm intelligence algorithms, operates iteratively using four fundamental components: the explosive operator, mutation operator, mapping rule, and selection strategy. These key building blocks play a critical role in facilitating dynamic exploration and guiding the algorithm towards optimal solutions (best PAPR value). The explosive operator is comprised of distinct sub-operators, including explosion strength associated with explosion amplitude, and shift mutation. Notably, the Gaussian mutation operator is a prevalent choice. On the other hand, the mapping rule offers multiple options, including the mirror and stochastic mapping rules. Finally, the selection strategy employs a blend of distance based and stochastic selection methods to determine the best candidates for the subsequent iterations [23]. The core of our approach revolves around the fusion of SLM and the FWA to discover the optimal phase vectors. In this scenario, the objective function aims to minimize the PAPR of the transmitted OFDM signals, and it can be expressed as in (7).

$$\begin{cases} \text{Minimize } f_{Obj}(x,\varphi) = \mathrm{PAPR}\{x[n]\} = \frac{\max\{|x[n]|^2\}}{E\{|x[n]|^2\}}, \quad 0 \le n \le NL-1 \\ \text{Subject to } x[n] = IDFT\left(X^{(u)}\right), \text{and } X^{(u)} = X\,.\,\varphi^{(u)} = \left[X_0^{(u)}, X_1^{(u)}, \dots X_{N-1}^{(u)}\right]^T \\ \varphi^{(u)} = \left\{\varphi_k^{(u)}\right\} = \left[\varphi_0^{(u)}, \varphi_1^{(u)}, \dots \varphi_{N-1}^{(u)}\right]^T, \ and \ \ \varphi_k^{(u)} = e^{j\varphi_k^{(u)}} \\ \varphi_k^{(u)} \in [0, 2\pi) \ \text{ for } k = 0,1,\dots,N-1 \text{ and } u = 1,2,\dots,U \end{cases} \tag{7}$$

The FWA workflow commences by creating an initial swarm of N fireworks randomly. Following this, every firework experience explosion and mutation procedures, and if necessary, the mapping rule is triggered to guarantee that sparks originate within the confines of the viable region [0, 2π]. Sparks are generated based on the influence of the explosive and mutation operators, and the selection strategy is employed to select the best sparks for the next generation. Iteration endures until the stipulated termination condition is achieved, leading to improved optimization results over time. The algorithm that follows outlines the step-by-step approach adopted by FWA in its quest to discover the best phase vector for PAPR reduction through SLM.

3.2. FWA and SLM for PAPR reduction

The forthcoming steps in Algorithm 1 unravel the methodological intricacies of our algorithm for PAPR reduction, a fusion of SLM and the innovative fireworks algorithm (FWA). This hybrid approach capitalizes on the strengths of both techniques to achieve a synergistic effect in mitigating the PAPR in OFDM systems. Algorithm 1, outlined below, delineates the systematic series of steps involved in optimizing PAPR reduction while addressing the computational complexities inherent in existing methods.

Algorithm 1. FWA-based SLM for PAPR reduction
```
1. Set the required input parameters, including stopping criterion, phase factors, and other relevant values.
2. Start the process by randomly picking n locations for the initial fireworks in the swarm.
3. Compute the fitness (PAPR) for each seed (firework). In (4)
4. While the stopping criteria are not met, do (continue the iterations)
5. Initiate N fireworks and set them off at their respective locations.
6. For every firework, do
7. Compute the number of sons it needs to generate.
8. Determine the amplitude/strength of each individual (sparks).
9. End for
   Generate m sparks using the Gaussian Mutation Operator for each firework.
10. For k=1:m; do
11. A firework φi is randomly chosen, and a spark is subsequently generated
12. Compute the fitness (PAPR) for each spark
13. End for
14. Use the selection strategy, utilizing the selection probability, to choose the most favorable sparks for the next iteration.
15. end while
```

4. RESULTS AND DISCUSSION
4.1. Parameters

In this section, we conduct a thorough performance evaluation of our proposed SLM based on FWA approach for reducing the PAPR in OFDM systems. We compare the effectiveness and efficiency of the SLM with FWA against other state-of-the-art techniques, including SLM with GA, SLM with PSO, and Original OFDM without PAPR reduction. The objective of this evaluation is to assess the performance of our novel approach regarding PAPR reduction and computational complexity. Extensive simulations are carried out under various scenarios and system settings to provide comprehensive insights into the performance of the proposed method.

We analyze the results, present the obtained PAPR reduction, and discuss the impact of each algorithm on the transmitted OFDM signals. Through this evaluation, we aim to demonstrate the potential of our proposed approach as an effective and efficient solution for reducing PAPR in OFDM systems. Table 1 encompasses a wide range of settings used to evaluate the performance of the new technique. These simulations have been conducted in accordance with the IEEE 802.11a and IEEE 802.16e standards to ensure relevance to real-world communication scenarios. These parameters include those specific to FWA, which were carefully selected based on preliminary experiments and are further detailed in [23], [24].

Table 1. Simulation settings

Parameter	802.11a (Wireless LAN)	802.16e (WiMAX)
FFT size	64	256
User carriers	52	200
Pilot carriers	4	8
Number of null/guard band subcarriers	12	56
Cyclic prefix or guard time	1/4, 1/8, 1/16, 1/32	
Modulation	QPSK, 3/4	
Oversampling factor	L=4	
Number of sub-blocks	V = 4	
phase factors	$\varphi = [0\ 2\pi]$	
population size n	5	
Gaussian mutation	5	
number of sparks (m)	50	
Parameters a and b	0.04 and 0.8	
$\widehat{m}$ and $\widehat{A}$	5 and 40	

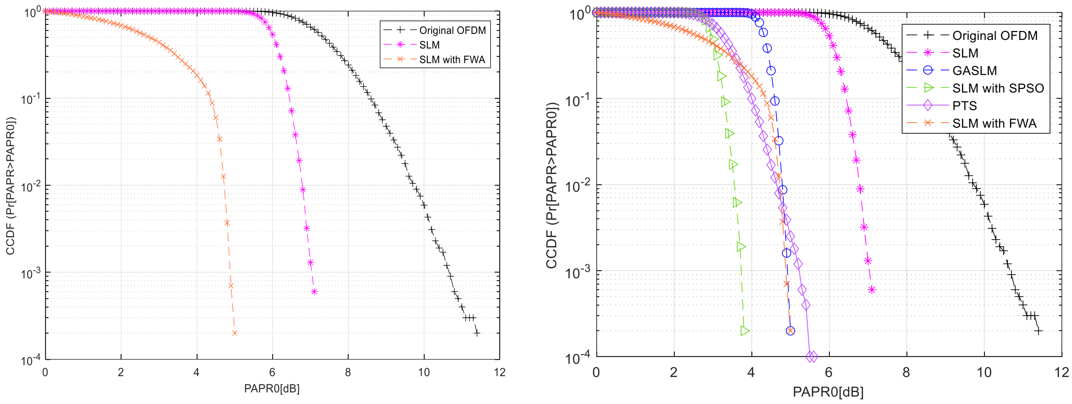
4.2. Performance analysis and comparison

Figure 2 encompasses a comparative analysis of PAPR reduction techniques employing different algorithms. In Figure 2(a), we illustrate the performance simulation of the SLM method based on fireworks algorithms. The OFDM system was simulated using 64 subcarriers. The simulation results demonstrate the effectiveness of the proposed method in reducing PAPR compared to the conventional SLM method. For instance, at a probability level of 10^{-3}, the PAPRs are 4.87 dB, 7.03 dB, and 10.6 dB for the FWA-based approach, the conventional SLM, and the original OFDM signals, respectively. The CCDF comparison in Figure 2(b) offers insights into the performance of optimization algorithms applied to the SLM technique. The simulations incorporate several optimization algorithms, including standard particle swarm optimization

(SPSO) [28], GA, and FWA, and compare them against conventional probabilistic methods of SLM and PTS, as well as the baseline scenario of original OFDM without PAPR reduction.

The results are promising, demonstrating that all the methods are effective in reducing PAPR. However, there are slight differences in their performance. Particularly, the SLM method enhanced by SPSO stands out as the most efficient, achieving a PAPR reduction of 3.7 dB at a CCDF of 10^{-3}. On the other hand, when SLM is combined with FWA and GA, it attains a commendable PAPR reduction of 4.875dB and 4.925 dB respectively (for CCDF=10^{-3}). Although PTS is effective, it exhibits a slightly higher value (5.2 dB). Meanwhile, the conventional SLM method and the original OFDM signals have 7.03 dB and 10.65 dB respectively. These results highlight the effectiveness of SLM-based approaches and the added value brought by optimization algorithms like SPSO, GA, and FWA. The marginal differences observed can be crucial in selecting the most suitable method for specific applications, depending on factors such as computational complexity and desired PAPR reduction levels.

In Figure 3, we illustrate the PAPR performance of the fireworks algorithm as the number of iterations in the algorithm varies. Specifically, it examines the impact of different maximum iteration value, including 3,000, 9,000, and 30,000, on the PAPR performance. As observed in the results (Figure 3), there is a notable trend in the PAPR performance with increasing iterations. With a maximum of 30000 iterations, the PAPR performance experiences significant improvement. For instance, at a CCDF of 10^{-3}, the PAPR is remarkably reduced to 1.9 dB when using 30,000 iterations. In contrast, the original OFDM signals exhibit a considerably higher PAPR value of 10.7 dB. It's important to note that while increasing the number of iterations in the FWA algorithm contributes to improving PAPR performance, however, this enhancement is accompanied by heightened computational demands. Therefore, the choice of the optimal number of iterations should be carefully considered in practical applications, balancing the desired PAPR reduction with computational efficiency.



(a) (b)

Figure 2. Comparative analysis of PAPR reduction techniques (a) FWA-based SLM for PAPR reduction and (b) comparison of PAPR reduction based on swarm intelligent algorithms

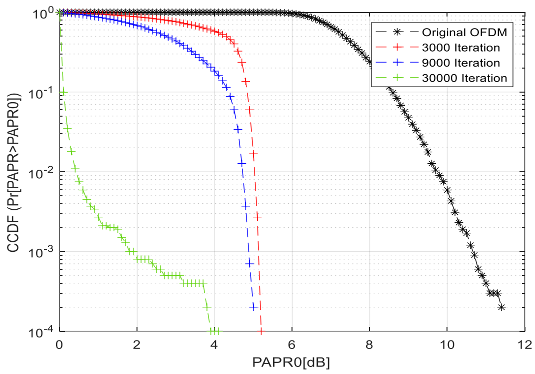


Figure 3. PAPR performance variations with iterations in FWA

4.3. Optimizing PAPR reduction for MIMO-OFDM

In this part, we take a closer look at the evaluation of the SLM technique based on the FWA within the framework of MIMO-OFDM system conforming to the WiMAX standard, as depicted in Figure 4. To streamline computations at the receiver end and amplify diversity gains on the transmission side, we have employed space-time block coding (STBC) with a two-transmit antenna setup following the Alamouti scheme. Our evaluation focuses on QPSK symbols that were generated randomly, and we have presented the complementary cumulative distribution function (CCDF) graphs for both the original and optimized signals in Figure 4(a). With the utilization of half-rate orthogonal STBC encoding across 10^4 OFDM symbols, the results are illuminating. The PAPR for the FWA-SLM method stands at a favorable 6.05 dB, unlike the 8.05 dB for the traditional SLM approach and a substantial 11.2 dB for the signal without any PAPR reduction technique.

In Figure 4(b), we investigate the performance of the three optimization algorithms (SPSO, GA, and FWA), in the context of MIMO OFDM systems. Each branch antenna of the transmit system is subjected to these optimization methods. The results reveal the efficacy of all three algorithms in significantly reducing the PAPR across the entire system. This figure offers important insights into how these optimization techniques affects the performance of MIMO-OFDM communication.

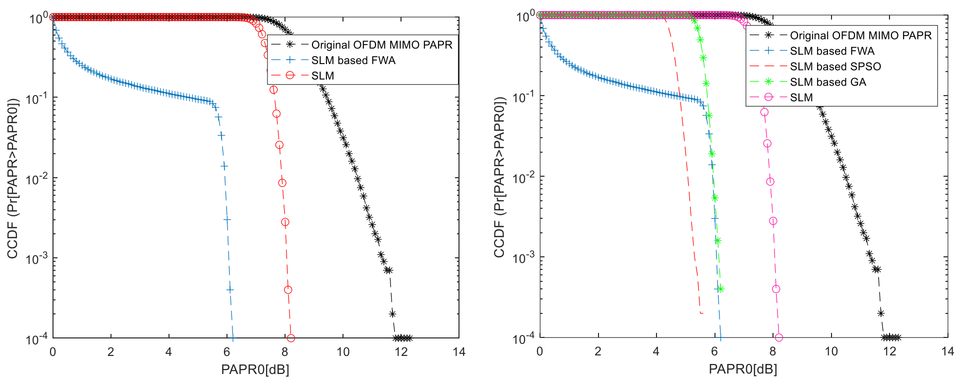


Figure 4. Comparative analysis of PAPR reduction techniques in MIMO OFDM systems (a) SLM based FWA and (b) comparison with optimization algorithms (SPSO, GA, and FWA)

4.4. Complexity comparison

This section provides a good analysis of the computational complexity and the convergence speed associated with various schemes employed to evaluate the performance of different optimization algorithms concerning PAPR reduction with reduced complexity. This analysis is crucial in understanding the trade-offs between PAPR reduction and computational complexity when employing different algorithms. Table 2, presents the computational complexity of different optimization algorithms (GA, SPSO, and FWA) at a CCDF of 10^{-3}. Notably, the genetic algorithm exhibits the highest PAPR value, measuring 5.84 dB, while keeping a relatively low complexity represented by the product of the maximum population size (P) and the generation count (G), equal to 500. Conversely, the SPSO method achieves the best PAPR reduction at 4.95 dB but requires a higher search number (S×Iter = 1,000), where, S is the population size and Iter is the maximum iteration number.

The SLM-based FWA approach falls in between, offering a PAPR value of 5.2 dB with a favorable search number. FWA's complexity is determined to be (Iter $*$ (n + m + $\hat{m}$)), amounting to 600. Where m is a parameter that regulates the overall number of sparks produced by the n fireworks, and $\hat{m}$ represents the count of sparks generated through gaussian mutation.

Table 2. Computational complexity assessment for PAPR Reduction Schemes at CCDF=10^{-3}

Methods	Number of searches	PAPR [dB]
Original	0	10.7
SLM-GA	P×G = 5×100 = 500	5.84
SLM-SPSO	S × Iter = 100×100 = 1,000	4.95
SLM-FWA	Iter × (n+m + $\hat{m}$) = 100× (5 + 50 + 5) = 600	5.2

Figure 5 illustrates the convergence speed of the fireworks algorithm in relation to GA and SPSO within the context of optimizing the PAPR of an OFDM symbol. The simulation is conducted using 3,000 iterations, and the results provide valuable insights into the trade-offs between convergence speed and PAPR reduction. The figure showcases that GA exhibits a notably faster convergence speed compared to SPSO and FWA. However, it's important to note that GA yields the highest PAPR value among the three algorithms. Conversely, FWA provides the most significant PAPR reduction, although it demands a comparatively higher number of iterations to achieve this optimal PAPR value. This figure helps in understanding the dynamic interplay between convergence speed and PAPR improvement when employing these optimization algorithms in OFDM systems.

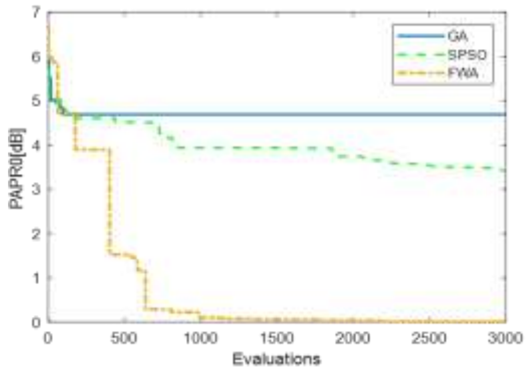


Figure 5. Convergence speed comparison of optimization algorithms

5. CONCLUSION

In the domain of OFDM systems, addressing the complex issue of PAPR has been a continuous endeavor. This study has explored a range of metaheuristic algorithms, Encompassing SPSO, GA, and the innovative FWA, integrated with the SLM technique. The results offer valuable understanding into PAPR reduction efficiency. Particularly, the FWA has emerged as a prominent candidate, showcasing its prowess in effectively reducing PAPR while maintaining reasonable computational complexity. The comparative analysis underscores the unique characteristics of each algorithm. PSO stands out for its speed and efficiency, achieving a PAPR reduction of 3.7 dB at a CCDF of 10^{-3}. GA also performs well with a PAPR reduction of 4.9 dB. FWA, although requiring more iterations, offers an attractive PAPR reduction of 4.87 dB. These findings highlight the versatility of these algorithms, catering to different application requirements. The study also extends its applicability to MIMO-OFDM systems, demonstrating that PAPR reduction techniques remain effective in multi-antenna setups. So, based on this study we can conclude that the choice of the most appropriate PAPR reduction approach should be aligned with the specific requirements of the application, taking into careful consideration computational requirements and the desired PAPR reduction goals.

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