

PAPR mitigation in GFDM using an efficient SLM technique based JAYA algorithm

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ABSTRACT

Significant research efforts have focused on selective mapping (SLM), a widely adopted technique for reducing the peak-to-average power ratio (PAPR) in multi-carrier communication systems. Although integrating SLM with metaheuristic optimization algorithms can significantly improve PAPR reduction, it generally introduces additional computational complexity due to the optimization process. To address this limitation, this paper proposes an improved SLM scheme, referred to as JAYA-SLM, for generalized frequency division multiplexing (GFDM) systems. The proposed approach employs the JAYA algorithm as an efficient phase-factor optimizer within the SLM framework, aiming to achieve an effective trade-off between PAPR reduction and computational complexity. The performance of JAYA-SLM is evaluated through extensive simulations and compared with conventional SLM-based GFDM, as well as SLM schemes assisted by artificial bee colony (ABC), genetic algorithm (GA), and biogeography-based optimization (BBO). Three low-complexity SLM variants are also considered for comparison. Simulation results demonstrate that the proposed JAYA-SLM achieves an average PAPR reduction of approximately 42% with rapid convergence and substantially lower computational complexity than conventional metaheuristic-assisted SLM approaches. Moreover, it provides notable power savings while maintaining an acceptable bit error rate (BER). These results confirm the potential of JAYA-SLM as an efficient and low-complexity PAPR reduction technique for GFDM-based 5G communication systems.

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1. INTRODUCTION

Advancements in modern technologies have significantly accelerated the emergence of diverse use cases, ranging from machine-type communications and smart urban infrastructure to the internet of things (IoT), cognitive radio networks, and large-scale device connectivity. These applications demand advanced and adaptable communication frameworks capable of supporting high data rates, reliability, and scalability [1]–[3].

As a result, they have driven significant research and development efforts toward fifth-generation (5G) wireless communication systems. In response, 5G is expected to fulfill stringent performance requirements, including enhanced quality of service, reduced latency, ultra-high data rates, and more efficient utilization of available spectral resources through advanced multicarrier transmission schemes [4], [5]. Data transmission is inherently relies on the deployment of multiple subcarriers due to the architecture of 5G networks. Numerous multicarrier modulation approaches have been investigated and suggested in the literature to satisfy the demanding requirements of 5G [6]. These modulation techniques are intended to provide high throughput with robust resistance to multipath fading and interference.

A non-orthogonal multicarrier system that is notable for its block-based structure is generalized frequency division multiplexing (GFDM) [7]–[9]. To improve resilience against inter-symbol interference (ISI), each GFDM frame is typically preceded by a single cyclic prefix (CP) [7]. Each GFDM block is formed by a predetermined number of symbols transmitted over multiple subcarriers. A tunable prototype filter is used in the GFDM design, which offers a straightforward yet incredibly adaptable framework for waveform shaping. Given its adaptability, GFDM enables higher spectral efficiency compared to conventional schemes [10]. Additionally, such filtering greatly reduces ISI and out-of-band (OOB) emissions, improving overall spectrum containment and transmission reliability [11].

As with other multicarrier modulation schemes, GFDM exhibits a relatively high peak-to-average power ratio (PAPR), which remains one of its primary challenges [12]. Elevated PAPR levels introduce nonlinear distortion, particularly within the transmitter power amplifier, leading to increased energy consumption and signal degradation. This distortion adversely affects system performance, notably impairing processes such as channel estimation. The resulting performance degradation is typically quantified using criteria such as symbol error rate (SER) and bit error rate (BER) [13].

To address the PAPR issue in 4G and next-generation wireless systems, various reduction techniques have been proposed and extensively studied [14]–[16]. These techniques are generally categorized into three main classes. The first class comprises distortion-based methods, with clipping and filtering being among the most widely used methods due to their simplicity and effectiveness in reducing PAPR. However, this approach inevitably introduces in-band distortion, which can significantly increase the BER. The second class includes coding-based schemes, such as those utilizing Zadoff-Chu sequences and Walsh Hadamard transforms [17], [18], which aim to reduce PAPR without introducing distortion by selecting symbol sequences that possess favorable power characteristics. The third category of PAPR reduction techniques consists of probabilistic methods. Partial transmit sequence (PTS) [19] and selective mapping (SLM) are two of the most prominent approaches [20]. These approaches aim to reduce PAPR by generating multiple signal representations and selecting the one with the lowest PAPR.

Many of these methods have been adapted for use in GFDM systems. In particular, several recent studies have investigated the application of SLM to GFDM. For instance, an SLM scheme tailored for GFDM was proposed in [21], demonstrating notable improvements in PAPR reduction. Similarly, Valluri and Mani [22] introduced a low-complexity version of the SLM technique, leveraging linear transformations and signal conversion to reduce computational cost. Simulation results confirm its effectiveness in lowering PAPR; however, the study did not examine its impact on BER and, therefore did not assess its influence on channel estimation accuracy. In another work, Bandari *et al.* [23] introduce a hybrid scheme integrating SLM with the Walsh transform, specifically designed for multi-taper GFDM. This method achieved substantial PAPR reduction while preserving signal integrity, i.e., without introducing distortion. Şimşir and Taşpınar [24] introduced an effective hybrid method designed to minimize PAPR in low-complexity GFDM systems. This approach integrated traditional SLM with a cumulative symbol optimization technique, yielding substantial PAPR reduction and enhancing the power spectral density (PSD) attributes of the transmitted signal.

Building on these advances, subsequent research has shifted to utilizing artificial intelligence (AI)-based optimization methods for PAPR reduction. Due to their versatility and efficacy in addressing complex optimization problems, AI-driven techniques have shown promising results in enhancing the efficiency of multicarrier communication systems. The present research in [20] introduced a pioneering hybrid scheme for mitigating PAPR, wherein cumulative symbol optimization is enhanced through the integration of conventional SLM and a chaotic biogeography-based optimization (CBBO) algorithm. This synergy leads to a marked reduction in PAPR, as demonstrated by the reported performance gains. Tuli *et al.* [25] proposes a computationally efficient approach for identifying appropriate phase rotation factors in universal filtered multicarrier systems. This approach combines the PTS strategy with the whale optimization algorithm (WOA), yielding a robust and

efficient solution. The suggested strategy outperforms the current PTS-based universal filtered multi-carrier (UFMC) method, resulting in a PAPR decrease of up to 4.5 dB at a complementary cumulative distribution function (CCDF) value of 10^{-3} . In addition to PAPR reduction, it also provides considerable improvements in BER and PSD. Tripathi *et al.* [26] present a PAPR reduction technique for OFDM systems that improves the PTS method using the improved salp swarm algorithm (ISSA). The proposed ISSA-based PTS significantly enhances the exploration and exploitation capabilities of the optimization process, leading to effective PAPR reduction. However, this improvement comes at the cost of a corresponding rise in BER and SER, as well as a slower convergence rate. Nanthamornphong *et al.* [27] present recurrent neural networks (RNNs)-PTS, a hybrid PAPR reduction approach that integrates RNNs with the traditional PTS architecture. The approach uses typical PTS phase rotation values while leveraging RNNs learning capabilities to improve selection efficiency. Simulation findings show that the suggested RNN-PTS technique effectively reduces PAPR while lowering computational complexity. Furthermore, the approach improves PSD performance while maintaining a favorable BER under Rayleigh fading conditions, particularly in filter bank multi-carrier (FBMC) systems.

Conventional methods often employ random or predefined phase sequences, which may not effectively suppress high signal peaks. To overcome this limitation, recent research [28] has investigated the use of structured mathematical constructs, such as the Riemann matrix, to generate phase sequences. In particular, normalized rows of the Riemann matrix have been proposed as phase sequence candidates, capitalizing on their favorable magnitude properties to mitigate peak power levels. This approach has shown promising results in enhancing PAPR reduction performance. Furthermore, to facilitate real-time implementation, efforts have been directed toward efficient side information (SI) management, aiming to minimize overhead while ensuring reliable signal reconstruction at the receiver. A novel nonlinear companding scheme is proposed in [29], specifically tailored to the GFDM signal structure, enabling effective PAPR reduction with minimal distortion. Additionally, the CCDF is analytically derived to investigate the influence of pulse-shaping filters on PAPR. By jointly optimizing companding parameters and filter design, significant improvements in PAPR performance are achieved. Simulation and USRP-based experimental results validate the effectiveness and practical applicability of the proposed approach. To address the high PAPR issue in GFDM systems, a modified error function companding (mEFC) technique was proposed in [30]. This method utilizes a companding parameter and a power scaling factor to suppress peak amplitudes while maintaining the average power, thereby avoiding dynamic gain adjustments in the power amplifier. Analytical expressions for the transform gain, attenuation factor, and achievable PAPR reduction have been derived to evaluate their effectiveness. Simulation results confirm that mEFC provides significant PAPR reduction and improved BER performance compared to conventional companding methods, demonstrating its suitability for practical GFDM-based communication systems.

Although existing methods such as particle swarm optimization (PSO), genetic algorithms (GA), ISSA [26], WOA, and CBBO [20], have demonstrated considerable improvements in PAPR reduction, they are often constrained by high computational complexity and the need for careful tuning of multiple control parameters. To overcome these limitations, the proposed approach leverages the JAYA algorithm, which is inherently simple and parameter-free. This feature reduces computational demands while retaining effective optimization capabilities. The proposed method integrates the conventional SLM approach with the JAYA algorithm, a swarm-based metaheuristic optimization technique. The JAYA algorithm has gained considerable attention in scientific and engineering domains due to its algorithmic simplicity, minimal parameter dependency, and effectiveness in solving both constrained and unconstrained optimization problems. By combining these two strategies, the proposed hybrid method aims to enhance PAPR reduction performance while maintaining low computational complexity [31], [32].

Furthermore, PAPR reduction plays a critical role in improving power amplifier efficiency, which directly affects the overall energy consumption of wireless communication systems. In the context of emerging 5G and IoT applications, where devices are often energy-constrained, efficient and low-complexity PAPR reduction techniques are essential. The proposed JAYA-SLM scheme, due to its parameter-free nature and reduced computational burden, offers a practical and scalable solution for real-time implementation, thereby supporting energy-efficient and sustainable wireless communication systems. Primary contributions of this research are highlighted as follows:

- a. This work proposes a low-complexity SLM scheme for GFDM systems based on the JAYA optimization algorithm to effectively reduce the PAPR. Unlike conventional metaheuristic-based SLM approaches such as GA, PSO, and ABC, the proposed method does not require any control parameters or hyperparameter tuning, which significantly simplifies the optimization process and reduces computational complexity.

- b. In the proposed approach, the JAYA algorithm is applied exclusively to optimize the phase sequence selection, enabling a straightforward implementation while maintaining strong convergence behavior. This makes the method particularly suitable for practical and real-time systems.
- c. The performance of the proposed method is evaluated in terms of BER under different signal-to-noise ratio (SNR) conditions and the achieved PAPR reduction. Extensive simulations are conducted and compared with conventional GFDM and GFDM-based ABC-SLM schemes to demonstrate the superiority of the proposed approach.
- d. The proposed scheme is also analyzed from a power efficiency perspective, showing that it contributes to reduced power consumption, which is essential for modern energy-efficient communication systems.
- e. Simulation results further indicate that the proposed JAYA-SLM method maintains superior performance even with an increasing number of subcarriers, demonstrating its scalability and robustness compared to existing techniques.

The organization of the paper is as follows. The GFDM-based system is introduced and discussed in section 2. The conventional SLM technique is presented in section 3. Details of the proposed JAYA-SLM algorithm, including a step-by-step explanation and mathematical formulation, are outlined in section 4, while an analysis of the computational complexity of the proposed technique is presented in section 5. Section 6 reports the simulation outcomes, and the conclusion is presented in section 7.

2. GENERALIZED FREQUENCY DIVISION MULTIPLEXING SYSTEM

In the framework of GFDM modulation, data transmission is organized into blocks consisting of M sub-symbols distributed over K subcarriers, forming a two-dimensional resource grid [33]. Each sub-symbol m is conveyed simultaneously on all subcarriers k , resulting in a composite block containing $N = K \times M$ modulated symbols. Figure 1 illustrates the architecture of a representative GFDM system, including the main processing stages, symbol mapping, subcarrier allocation, pulse shaping, transmission over the channel, and receiver-side demodulation and detection.

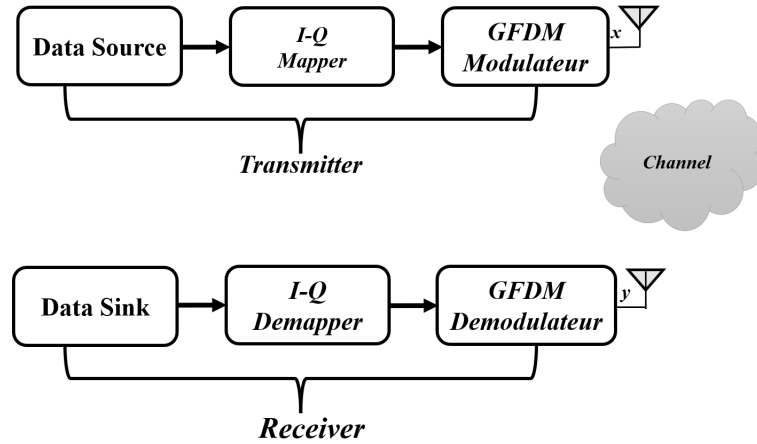


Figure 1. Block diagram of a GFDM transceiver system

Initially, the incoming binary data stream is modulated using QAM, resulting in a sequence of complex-valued symbols. These symbols are arranged into a data vector $\vec{d}$, structured as (1):

$$\vec{d} = d_{0,0}, d_{1,0}, \dots, d_{K-1,M-1} \quad (1)$$

Each complex-valued data sub-symbol $d_{k,m}$, undergoes circular pulse shaping using a root raised cosine (RRC) filter. This process ensures spectral confinement and minimizes ISI. The circular convolution is applied as (2):

$$g_{k,m} = g[(n - mK)_{\text{mod}N}] \exp(j2\pi \frac{kn}{K}), \quad n = 0, \dots, N-1, m = 0, \dots, M-1 \quad (2)$$

The discrete time index within the GFDM blocks is denoted by n . Consequently, the complete GFDM modulated signal is denoted as (3):

$$x[n] = \sum_{k=0}^{K-1} \sum_{m=0}^{M-1} d_{k,m} g_{k,m}[n] \quad (3)$$

The combined effect of pulse shaping across all subcarriers and sub-symbols can be compactly represented using a modulation matrix A , which encapsulates the time-domain contributions of each data symbol $d_{k,m}$. This matrix maps the data vector to the transmit signal x as (4):

$$A = [g_{0,0} \dots g_{K-1,0} \dots g_{0,1} \dots g_{K-1,M-1}] \quad (4)$$

Accordingly, the GFDM modulation matrix is denoted by $A \in \mathbb{C}^{N \times N}$, where d is expressed as a column vector. As a result, the GFDM modulator output is given by (5):

$$x = Ad. \quad (5)$$

The transmitted signal x propagates through an additive white Gaussian noise (AWGN) channel. Accordingly, the expression for the received signal y is given by (6):

$$y = Hx + w \quad (6)$$

In this context, the channel is modeled by a circulant convolution matrix H , derived from the impulse response h , which is assumed to be ideal (i.e., $h = 1$). The term w represents complex AWGN noise. The receiver employs zero-forcing (ZF) for signal reconstruction to counteract channel distortions and retrieve the original transmitted data, where the equalization matrix is given by $B_{ZF} = A^{-1}$. Accordingly, the estimated data vector $\tilde{d}$ is obtained as (7):

$$\begin{aligned} \tilde{d} &= B_{ZF}y \\ &= B_{ZF}Ad + B_{ZF}w \end{aligned} \quad (7)$$

Here, B_{ZF} denotes the receiver matrix implementing the ZF equalizer, and d represents the GFDM data block estimated through linear demodulation. Based on the formulation in (3), the PAPR expression for the GFDM multicarrier system is expressed as (8):

$$PAPR(\text{ dB}) = 10 \log_{10} \left(\frac{\max_{0 \leq n < K \times M} |x_{cp}(n)|^2}{\mathbb{E}[|x_{cp}(n)|^2]} \right) \quad (8)$$

$x_{cp} = x[x(MK - N_{cp} + 1 : MK); MK]$, N_{cp} represents the CP sample length, $\max_{0 \leq n < K \times M} |x_{cp}(n)|^2$ corresponds to the maximum power reached by the GFDM signal, $\mathbb{E}[|x_{cp}(n)|^2]$ refers to the average expected value of $|x_{cp}(n)|^2$. Furthermore, the PAPR $x_{cp}(n)$ is assessed through CCDF, which describes the probability that the PAPR exceeds a predefined threshold $PAPR_0$. Accordingly, the CCDF can be formulated as (9):

$$\begin{aligned} CCDF(PAPR\{x(n)\}) &= Pr(PAPR(X) > PAPR_0) \\ &= 1 - (1 - e^{-PAPR_0})^N \end{aligned} \quad (9)$$

High PAPR in GFDM modulation poses a significant problem because it leads to increased OOB spectral components, resulting in diminished spectral efficiency of the system. Therefore, effective PAPR mitigation techniques are required. Stochastic methods, including SLM, are commonly employed for this purpose, owing to their ability to maintain an optimal balance between BER performance and PAPR. However, the effectiveness of SLM largely depends on the choice of phase patterns. In this work, SLM is combined with the JAYA algorithm to optimize phase selection and enhance PAPR reduction.

3. CONVENTIONAL SELECTIVE MAPPING METHOD

In GFDM modulation, the SLM technique aims to mitigate PAPR by generating U distinct candidate signal sequences derived from a single data block. Transmission is performed using the sequence resulting in the lowest PAPR. This method exploits the strong dependency of PAPR on the ordering and phase rotation of data vectors: small perturbations in the input phase distribution can lead to substantially different time-domain amplitude envelopes. An illustration of this concept is provided in Figure 2.

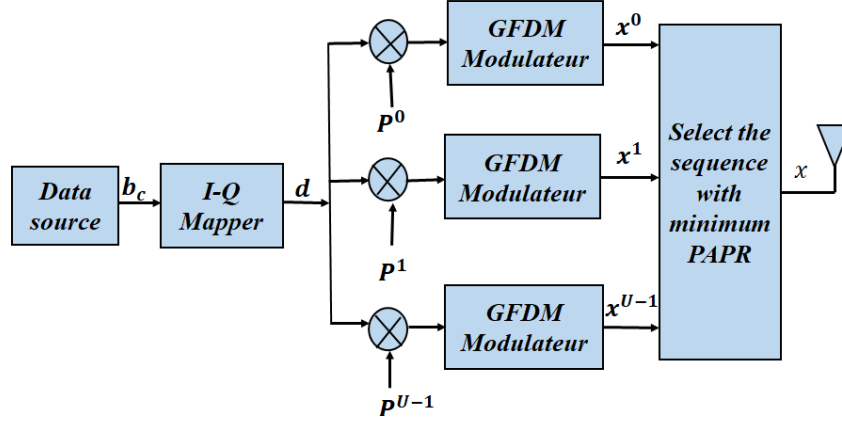


Figure 2. Structural framework of the conventional SLM approach for PAPR reduction in GFDM systems

The SLM procedure begins by applying U independent random phase sequences to the input data block. The data vector $d \in \mathbb{C}^{MK \times 1}$ contains K subcarriers each carrying M subsymbols, where the total block length is $N = MK$. Each candidate phase vector $P_u \in \mathbb{C}^{MK \times 1}$, for $u = 1, 2, \dots, U$, is element-wise applied to d to produce a phase-rotated data block. The resulting candidate transmitted signal is obtained by passing the rotated block through the GFDM modulator matrix A , and can be expressed mathematically as [21], [34]:

$$x^u = A * (P_u \circ d) \quad (10)$$

Where $\circ$ denotes the Hadamard (element-wise) product applied between phase rotation vector P_u and the data vector d . The elements of P_u are drawn from the set $\{\pm 1, \pm j\}$, a design choice that enables low-complexity hardware implementation by replacing general complex multiplications with simple sign and index inversions. The modulation matrix $A \in \mathbb{C}^{N \times N}$ encapsulates the GFDM pulse-shaping and subcarrier mapping operations, such that the product $A(P_u \circ d)$ yields the time-domain baseband signal for the u_{th} candidate. Once all U candidate signals $\{x^u\}_{u=1}^U$ have been generated, the PAPR of each candidate is evaluated as (11):

$$\text{PAPR}(x^u) = \frac{\max_n |x^u[n]|^2}{\mathbb{E}[|x^u[n]|^2]}, \quad u = 1, 2, \dots, U \quad (11)$$

The optimal candidate index $\hat{u}$ is then selected as (12):

$$\hat{u} = \arg \min_{u \in \{1, \dots, U\}} \text{PAPR}(x^u) \quad (12)$$

The receiver must be informed of the selected phase index $\hat{u}$ in order to reverse the phase rotation and correctly recover the original data. This overhead, known as SI, must be transmitted reliably alongside the data and represents the primary practical drawback of the conventional SLM method. The SI introduces additional bandwidth consumption and becomes increasingly costly as the number of candidates U grows, since $\lceil \log_2 U \rceil$ bits are required per data block to encode the selected index.

The overall PAPR reduction performance improves with increasing U , as a larger candidate pool provides a better probability of finding a low-PAPR signal. However, this increases computational complexity, as U independent GFDM modulations must be carried out for each data block.

4. THE PROPOSED PEAK-TO-AVERAGE POWER RATIO REDUCTION TECHNIQUE

4.1. JAYA algorithm

The JAYA algorithm employs a heuristic search strategy driven by stochastic principles. Introduced by [35], [36], has been effectively utilized for addressing optimization problems with or without constraints [37]. Furthermore, the algorithm requires no specialized control parameters beyond the standard ones common to most optimization algorithms, including parameters such as design variable, population size, and the iteration count. Another key advantage is the straightforwardness of its implementation. Collectively, this aspect significantly reduces time and effort involved in locating the optimal solution.

By incorporating the JAYA algorithm, an optimal solution can be efficiently obtained, enabling the resolution and scientific and engineering challenges while maintaining the simplicity of the search process. This method functions on the principle that searching particles progressively distance themselves from suboptimal solutions (i.e., failures) and converge towards optimal solutions (i.e., successes). The JAYA algorithm employs a simple, single-phase process to achieve the optimal solution. Its procedure is illustrated in the flowchart presented in Figure 3.

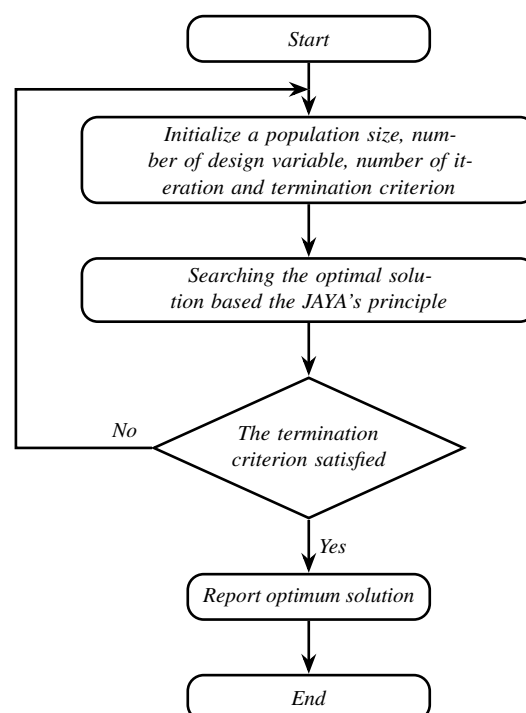


Figure 3. Flowchart of the JAYA optimization algorithm, illustrating how candidate solutions are iteratively updated by moving closer to the best solution and farther from the worst one

4.2. Modified JAYA algorithm-based selective mapping scheme

Addressing the high PAPR in GFDM systems, the conventional SLM technique is employed. However, one of the major difficulties with the SLM approach is achieving the ideal phase with less complexity and simplicity. Therefore, the primary objective of our suggested method is to improve PAPR performance with less complexity and high simplicity by combining the JAYA algorithm with the conventional SLM method. Alongside other established algorithms, including SLM-GA [38], ABC-SLM [39], and SLM-PSO [40], the JAYA algorithm [35] is introduced in this work to mitigate the system's complexity arising from the implementation of SLM in combination with optimization algorithms. The proposed JAYA-SLM technique utilizes a single phase optimization process and operates without necessity of hyperparameters. Additionally, to achieve lower PAPR in the GFDM system, the JAYA algorithm employs a set of search agents to find the best combination in the SLM scheme. However, in order to address the continuous optimization problem using the JAYA algorithm, particular conversions are necessary. The suggested approach is depicted in Figure 4.

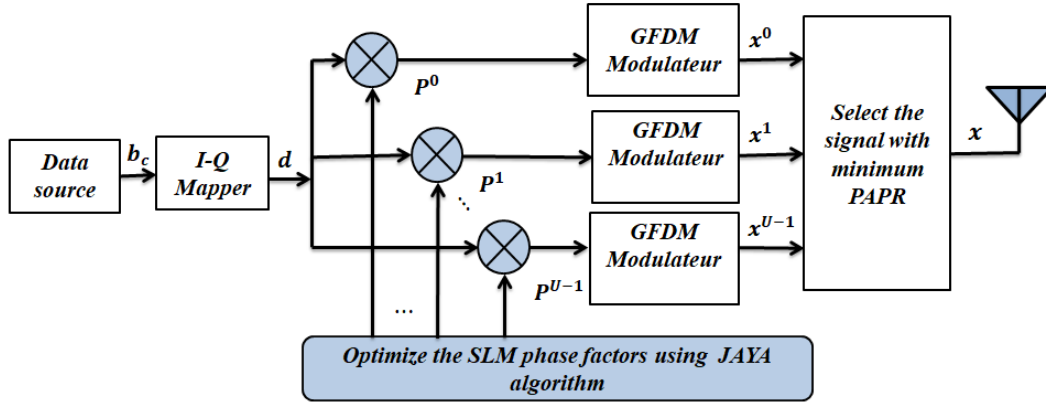


Figure 4. Block diagram of the proposed GFDM-based JAYA-SLM system, where the JAYA algorithm optimizes phase sequences for PAPR reduction

The fundamental idea behind the JAYA-SLM algorithm is that each particle $P_{N,i}$ ($i = 1, 2, \dots, SN$) corresponds to a phase factor utilized in the SLM scheme. Here, the population size SN is denoted and maintained throughout the search iterations in the proposed method. In this approach, the phase elements are selected from the set $P = [-1, 1]$. The following steps outline the modified JAYA-based SLM optimization process:

Phase 1: this phase involves generating an initial random phase sequence $P_{N,i}$, followed by the immediate evaluation of its fitness using the defined objective function:

$$fit(P_{N,i}) = \frac{1}{1 + PAPR(P_{N,i} * x)} \quad (13)$$

As shown in (13), the fitness value improves as the PAPR decreases.

Phase 2: in this stage, the best and worst solutions are determined from the initial population. The phase factor with the highest fitness value and the lowest PAPR is selected as the best solution, whereas the one with the lowest fitness value and the highest PAPR is identified as the worst solution. These extreme solutions are denoted by $P_{N,best}$ and $P_{N,worst}$, respectively. Subsequently, new candidate solutions for all phase factors are generated by applying the JAYA update rule, as expressed in (14):

$$P'_{N,i} = P_{N,i} + r_{1,i}(P_{N,best} - |P_{N,i}|) + r_{2,i}(P_{N,worst} - |P_{N,i}|) \quad (14)$$

$P_{N,i}$ is updated to $P'_{N,i}$, with $r_{1,i}$ and $r_{2,i} \in [0,1]$ denoting random values sampled from a uniform distribution. The term $r_{1,i}(P_{N,best} - |P_{N,i}|)$ represents the inclination to approach the optimal solution, while $r_{2,i}(P_{N,worst} - |P_{N,i}|)$ denotes the strategy to prevent suboptimal solution. Given that $P'_{N,i}$ represents a candidate solution in a discrete phase, (15) is revised according to the following condition:

$$P'_{N,i,j} = \begin{cases} 1 & , if \frac{\pi}{4} \leq P'_{N,i,j} \leq \frac{5\pi}{4} \\ -1 & , else \end{cases} \quad (15)$$

Phase 3: in each j_{th} iteration, the candidate solutions $P_{N,i}$ are updated accordingly. The fitness value of the newly generated solution, $fit(P'_{N,i})$, is subsequently evaluated using the objective function defined in (13). A greedy selection strategy is then employed, whereby the updated solution is accepted if $fit(P'_{N,i}) > fit(P_{N,i})$; otherwise, the existing solution $P_{N,i}$ is preserved.

Phase 4: steps 2 and 3 of the proposed JAYA-SLM approach are repeated iteratively until the predefined maximum number of iterations is reached. An overall representation of the proposed PAPR reduction technique, referred to as the JAYA-SLM strategy, is shown in the block diagram in Figure 5.

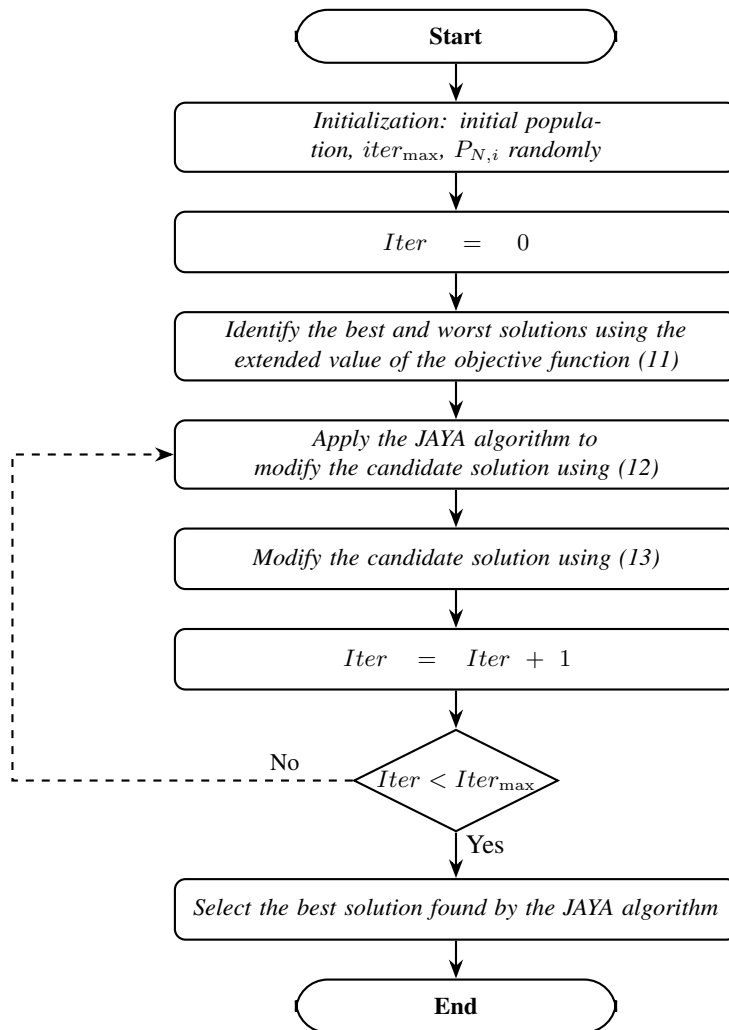


Figure 5. Flowchart of the proposed JAYA-SLM algorithm for PAPR reduction

4.3. Complexity analysis of the proposed method

The following analysis evaluates the computational complexity of the proposed method in a GFDM system. The overall complexity depends on several parameters, including the number of phase sequence candidates U , the number of subcarriers K , the number of sub-symbols M , as well as the additional computational overhead introduced by the optimization algorithms. In the SLM scheme, the main source of complexity comes from generating multiple alternative candidate signals, each requiring circular convolution with the pulse-shaping filter. This filtering operation is the most computationally intensive step and is generally implemented using FFT-based circular convolution, with a complexity of $O(KM \log(KM))$. Consequently, for U candidate sequences, the overall computational complexity of the SLM-based PAPR reduction method is given by (16):

$$O(U \times K \times M \times \log(KM)) \quad (16)$$

As the number of phase rotation sequences in the set of U candidates increases, the achieved PAPR performance generally improves; however, this improvement comes at the expense of a higher computational load required for PAPR evaluation. To mitigate the exhaustive search problem inherent in conventional selected mapping (SLM) techniques, several researchers have adopted metaheuristic optimization strategies. In this context, the JAYA-based SLM approach has been introduced as an efficient alternative. Although this method eliminates the need for an exhaustive search, it still introduces additional computational overhead due to its iterative optimization procedure. The overall computational complexity of the JAYA-SLM scheme can be

formulated as (17):

$$O(iter_{max} \times SN \times K \times M \times \log(K \times M)) \quad (17)$$

Where $iter_{max}$ is the maximum number of iterations and SN is the population size. The JAYA algorithm itself performs $O(iter_{max} \times SN)$ operations without requiring any algorithm-specific control parameters, making it relatively simple to implement. Another commonly used metaheuristic algorithm in the literature is the ABC algorithm. The ABC-SLM technique involves three optimization phases: i) the employed bee, ii) the scout bee, and iii) the onlooker bee. Additionally, it includes a tuning parameter called the limit value. As described in [41], [42], the algorithm operates through four main steps. Where the complexity of ABC-SLM is defined as (18):

$$O(3cyc \times SN \times K \times M \times \log(K \times M)) \quad (18)$$

Here, cyc and S represent iteration count and the population size, respectively. A summary of complexity is presented in Table 1.

Table 1. Complexity analysis of PAPR reduction techniques

Technique	Computational complexity	Remarks
SLM	$O(U \times K \times M \log(KM))$	1. Complexity: moderate complexity due to exhaustive search over U candidates. 2. Convergence: non-iterative, selection-based. 3. Runtime: increases linearly with U . 4. Required: U predefined phase sequences.
JAYA-SLM	$O(iter_{max} \times SN \times K \times M \log(KM))$	1. Complexity: depends on the number of iterations. 2. Convergence: fast, iterative metaheuristic search [32]. 3. Runtime: high; depends on $iter_{max}$ and SN . 4. Required: U phase sequences, no parameter tuning.
ABC-SLM	$O(3 \times cyc \times S \times K \times M \log(KM))$	1. Complexity: high complexity from multi-phase process (employed, onlooker, scout bees). 2. Convergence: slower due to multi-phase design. 3. Runtime: high; affected by cyc and swarm size S . 4. Required: U phase sequences and tuning (limit).

5. SIMULATION RESULTS

This section presents the simulation results used to evaluate the performance of the proposed PAPR reduction technique in a GFDM system. The effectiveness of the method is examined and compared with the conventional SLM scheme for different values of the search number SN . In addition, the influence of the number of subcarriers on the proposed approach is investigated. In the JAYA-based SLM scheme, the parameter SN represents the number of randomly generated phase sequences used in conventional SLM, which is denoted by U . For simplicity, the phase rotation factors employed in the JAYA-SLM optimization process are restricted to the set $P = [-1, 1]$. The performance of the considered schemes is assessed in terms of PAPR, BER, and power saving. Furthermore, a comparative study between the proposed JAYA-SLM and the ABC-SLM algorithm is carried out with respect to PAPR reduction capability, BER performance, and convergence behavior. A summary of the simulation parameters is given in Table 2. Other parameters, such as the search interval and the number of subcarriers, are specified in the respective figure captions. All simulations are implemented in MATLAB, where a total of 100,000 GFDM blocks are generated for analysis.

Table 2. Simulation parameters

Parameter	Value
Number of subcarriers (K)	$\in 64, 128, 256, 660$
GFDM subsymbols (M)	5
Modulation type	QPSK (4-QAM)
SNR range	0–20 dB
Channel model	AWGN
Population size (JAYA)	$\in (2, 4, 16, 64)$
Number of iterations	100
CP ratio	$\frac{1}{8}$
Pulse shaping filter	RRC ($\alpha = 0.5$)

5.1. Performance analysis of the peak-to-average power ratio reduction via JAYA-selective mapping

In the following, we analyze the PAPR performance by utilizing the CCDF, which indicates the likelihood that the PAPR of the GFDM signal surpasses a specified level, denoted as $PAPR_0$. A fair comparison is conducted between the proposed JAYA-SLM and conventional SLM under similar conditions. The number of search phases used in the simulation outcomes is denoted by SN . The performance of the suggested method and baseline SLM is illustrated in Figure 6, where the CCDF is plotted against PAPR with the number of search phases set to $SN = 2$.

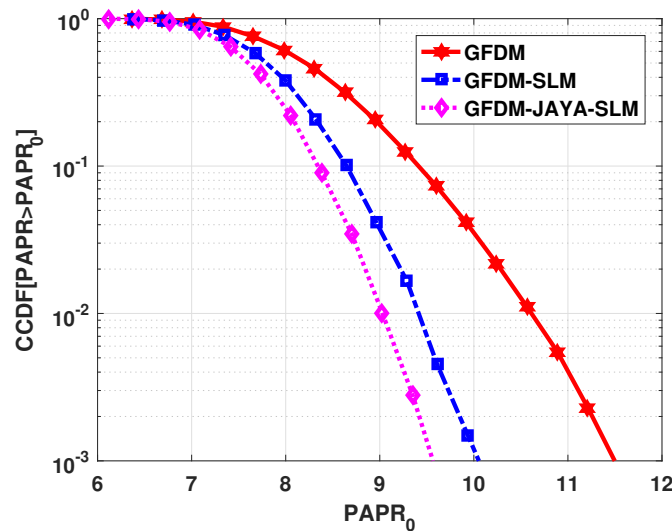


Figure 6. Comparison of PAPR in 4-QAM GFDM using JAYA-SLM ($K = 64$, $SN = 2$, and $\alpha = 0.5$)

As depicted in Figure 6, the proposed JAYA-SLM achieves a lower PAPR compared to conventional SLM. This improvement is attributed to the search mechanism of the JAYA algorithm which avoids the worst phase sequences and selects the optimal ones, thereby effectively mitigating unwanted peaks. At the CCDF level of 10^{-3} , while the baseline GFDM framework exhibits a PAPR of 11.5 dB and the conventional SLM reduces it to 10.5 dB. In contrast, the proposed JAYA-SLM approach further lowers the PAPR to 9.5 dB. These results demonstrate that integrating the JAYA algorithm with SLM significantly enhances the search capability of SLM technique and improves its overall PAPR reduction performance. Population size is a key metric in optimization algorithms, and its impact is particularly relevant in PAPR reduction schemes. In this context, Figure 7 illustrates the effect of varying the number of phase sequences $SN = 4, 16, 64$, simulation outcomes are evaluated for the proposed method alongside the conventional SLM approach and the original GFDM signal.

As shown in this Figure 7, the proposed technique consistently achieves superior PAPR reduction across all SN values. For instance, at a $CCDF = 10^{-3}$, the original GFDM signal exhibits a PAPR level close to 11.8 dB. In comparison, the conventional SLM approach yields PAPR values of 9.4 dB, 8 dB, and 7.4 dB for $SN = 4$ to $SN = 64$, respectively. The proposed technique further improves these results, achieving lower PAPR values of 8.7 dB, 7.6 dB, and 6.9 dB for corresponding SN values. Overall, the suggested method decreases the PAPR by up to 4.6 dB compared to the original GFDM signal and demonstrates consistent improvement over the existing SLM method. This improvement is attributed to the increased likelihood of identifying sequences with lower PAPR as the number of candidate sequences grows. However, as discussed in subsection 5.5, this improvement introduces computational overhead. Specifically, raising the number of random phase factors raises the complexity inherent in the system, highlighting a trade-off between performance and computational efficiency.

Supporting a large number of subcarriers is essential for achieving high data rates in modern wireless networks. In this regard, our study investigates the impact of the number of subcarriers K over the suggested method. Figure 8 illustrates the impact of varying the number of subcarriers on PAPR efficiency, using values $K = 64, 128, 256, 660$ and a fixed number of search phases $U = 4$. Based on this figure, the proposed method consistently improves PAPR reduction performance, even as total number of subcarrier rises. For instance, at the CCDF level 10^{-3} , the baseline GFDM framework exhibits PAPR values of approximately 11.8 dB, 11.5 dB, 12.2

dB, 12.8 dB, and 12.5 dB for $K = 64, 128, 256, 660$, respectively. In contrast, the proposed technique reduces these values to 8.8 dB, 8.9 dB, 9.4 dB, 10.2 dB, and 10.4 dB, respectively. These results highlight the robustness of the proposed technique, even with increasing number of subcarriers, PAPR increases by only about ± 1 dB.

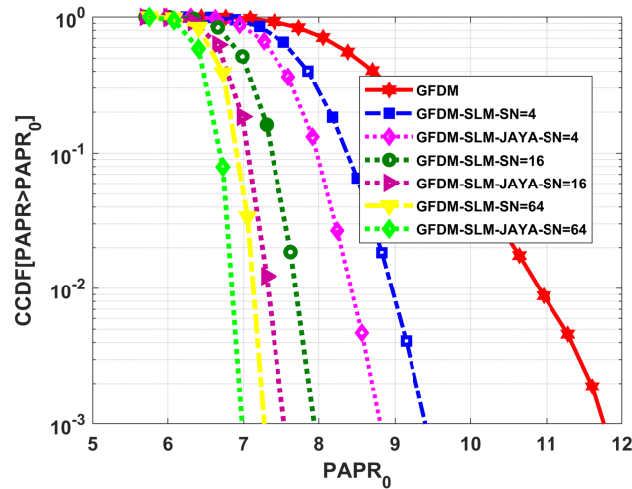


Figure 7. CCDF of PAPR for the proposed GFDM-SLM-JAYA scheme with varying numbers of phase sequences ($SN = 4, 16, 64$), evaluated for 4-QAM modulation with K subcarriers

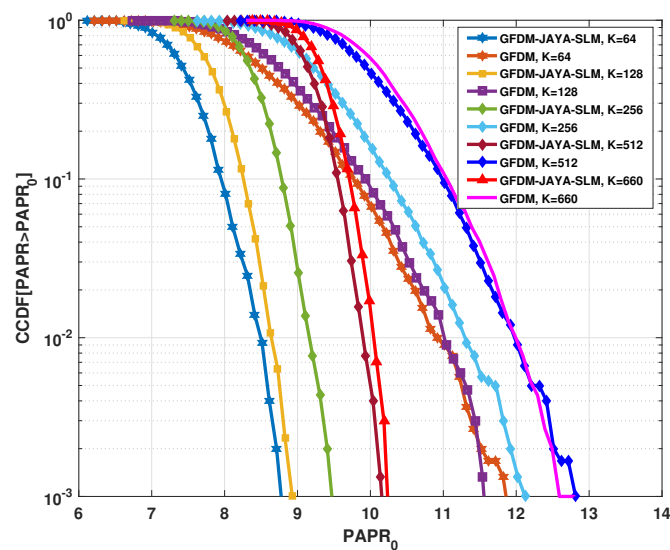


Figure 8. The influence of different number of subcarrier on the PAPR reduction effectiveness of the suggested GFDM-SLM-JAYA $K = 64, 128, 256, 660$, (4-QAM, $M = 5$, $\alpha = 0.5$, $SN = 4$)

This stability is significant as it suggests the technique can effectively supports a large number of subcarriers without suffering from the typical PAPR degradation seen in conventional OFDM systems where PAPR tends to grow with the number of subcarrier. This characteristic is particularly advantageous for current and next-generation wireless networks. For instance, LTE systems support up to 2048 subcarriers [43], and 5G systems aim to handle up to 3300 subcarriers [6]. Within the GFDM framework, this corresponds to a configuration with $K = 660$ subcarriers and $M = 5$ sub-symbols, demonstrating that GFDM can flexibly accommodate high subcarrier densities while maintaining favorable PAPR performance. This improvement

contributes to enhancing the efficiency of the power amplifier and effectively reduces signal distortion, thereby making the suggested method well-suited for high spectral efficiency while satisfying tight latency constraints of LTE and 5G systems.

To evaluate the efficiency of the suggested JAYA-SLM scheme, Table 3 compares the PAPR reduction at a CCDF level of 10^{-3} for $SN = 64$, alongside the GA-SLM and BBO-SLM techniques reported in [20]. As indicated in Table 3, the proposed JAYA-SLM method demonstrates a notable improvement over both BBO-SLM and GA-SLM. Specifically, BBO-SLM achieves a 41% reduction in PAPR, GA-SLM achieves 39%, while the proposed JAYA-SLM attains a 42% reduction. Moreover, the proposed JAYA-SLM technique requires only a single phase to update phase sequences, unlike GA-SLM and BBO-SLM, which involve multiple iterative updates, and control parameters such as mutation rate and mutation probability. A further comparison is made with three enhanced low-complexity SLM techniques SLM1, SLM2, and SLM3 using a phase sequence size of $SN = 16$, as presented in [22]. As shown in Table 3, SLM1, SLM2, and SLM3 achieve PAPR reductions of 31%, 36%, and 33%, respectively, whereas the proposed method achieves a significant reduction of 37%, demonstrating its effectiveness and efficiency.

Table 3. Comparison of PAPR reduction techniques at CCDF = 10^{-3}

Technique name	SN	PAPR ref. value (dB) at $CCDF = 10^{-3}$	PAPR reduction (dB) at $CCDF = 10^{-3}$	Improvement (%)
GA-SLM [20]	64	9.9	6	39
BBO-SLM [20]	64	9.9	5.8	41
Proposed	64	11.8	6.9	42
SLM1 [22]	16	10.8	7.4	31
SLM2 [22]	16	10.8	6.9	36
SLM3 [22]	16	10.8	7.2	33
Proposed	16	10.8	7.5	37

Regarding the GFDM system, the proposed JAYA-SLM technique targets a reduction in the PAPR by optimizing phase factors using the JAYA algorithm, thereby selecting the optimal phase factors efficiently. In contrast, the ABC algorithm is a widely recognized optimization technique for mitigating PAPR, often combined with other methods such as PTS and SLM. The ABC-based SLM approach involves three main phases. First, the employed bees select the best phase factors. Then, based on selection probability, the onlooker bees update these factors. Finally, if a solution is not improved within a certain limit L , it is updated by the scout bees. The limit is computed using the following formula $L = \frac{pop \times D}{2}$, where pop denotes the total number of phase factors applied, while D denotes the number of GFDM signals. To assess performance, the PAPR mitigation capability of the suggested JAYA-SLM method is contrasted with the ABC-SLM approach in Figure 9.

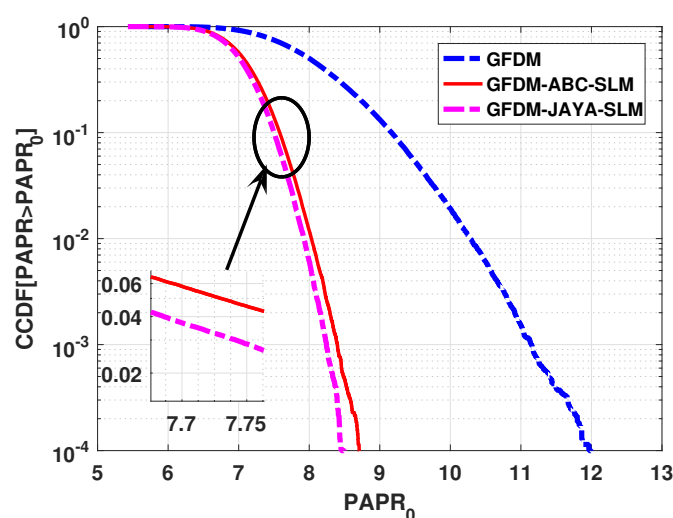


Figure 9. Comparative CCDF analysis of PAPR for JAYA-SLM, ABC-SLM, and conventional SLM

To ensure a fair comparison, both algorithms are evaluated under identical simulation conditions, a population of size $SN = 2, 64$ subcarriers, and 20 iterations. As shown in the figure, the proposed JAYA-SLM method achieves superior PAPR reduction. For example, at $CCDF = 10^{-4}$, the JAYA-SLM achieves 8.5 dB, while the ABC-SLM achieves 8.9 dB. Notably, the JAYA-SLM accomplishes this with only a single optimization phase, unlike the three optimization phases required in the ABC-based method, highlighting its computational efficiency.

5.2. Evaluation of root mean square error performance

The proposed JAYA-SLM scheme's accuracy and stability are evaluated using the RMSE as a performance parameter. RMSE is a quantitative measure of the variance between the estimated and reference signals, defined as (19):

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - \hat{x}_i)^2} \quad (19)$$

Where x_i denotes the reference signal and $\hat{x}_i$ denotes the estimated signal. Figure 10 demonstrates the effect of the search number ($SN = 2, 4, 16, 64$) on the RMSE performance of the proposed system for $K = 64$ subcarriers. It is evident that augmenting the search quantity markedly enhances RMSE performance. A greater search number improves the exploratory capacity of the JAYA algorithm, resulting in more precise phase sequence selection. Specifically, the RMSE of GFDM-SLM is generally stable around 2, showing consistent estimation accuracy. In comparison, the GFDM-JAYA-SLM scheme exhibits higher RMSE values which increase with the number of phase sequences. Its structure indicates that, while JAYA-based optimization enhances search capabilities, it may introduce more variability, reducing estimation accuracy. Furthermore, when SN rises, the difference between the two techniques increases. This demonstrates a trade-off between optimization complexity and estimating precision in the proposed approach.

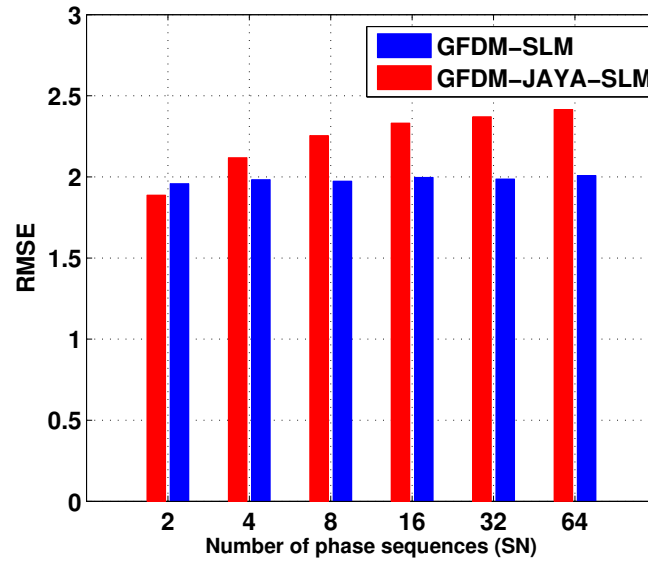


Figure 10. Effect of search number ($SN = 2, 4, 16, 64$) on RMSE performance for the JAYA-SLM scheme with $K = 64$ subcarriers

5.3. Evaluation of power saving performance

The power saving is a critical metric in wireless communication systems, driven by the need for the energy-efficiency transmission, prolonged device battery life, and reduced operational costs, particularly in high-data-rate application, such as LTE and 5G. Power savings are closely related to the PAPR of the transmitted signal. The relationship is particularly important for wireless transmission systems, as lower PAPR allows

power amplifiers to operate more efficiently, thereby reducing energy consumption. In general, the lower the PAPR, the greater the power saving at the transmitter. In this regard, we evaluate the power saving achieved by the suggested method under various numbers of subcarriers and phase sequences. The power saving metric is defined as (20) [44], [45]:

$$P_s = \frac{P_o - P_T}{P_o} * 100 \quad (20)$$

As illustrated in Figure 11, the power saving efficiency of the suggested technique is evaluated by varying the number of phase sequences $SN = 2, 4, 16, 64$ while keeping the number of subcarriers fixed at 64. The results clearly indicate that the suggested approach achieves notable power savings compared to the conventional SLM method. Specifically, the proposed technique achieves power savings of 18.8%, 20%, 36.36%, and 37.27% , respectively, for $SN = 2, 4, 16, 64$ under the same conditions. This demonstrates the superior performance of our proposed method, particularly at higher numbers of phase sequences. The observed enhancements in power saving directly contribute to improving power amplifier, thereby making the proposed technique especially well-suited for energy-constrained wireless communication systems, such as those used in 5G and IoT.

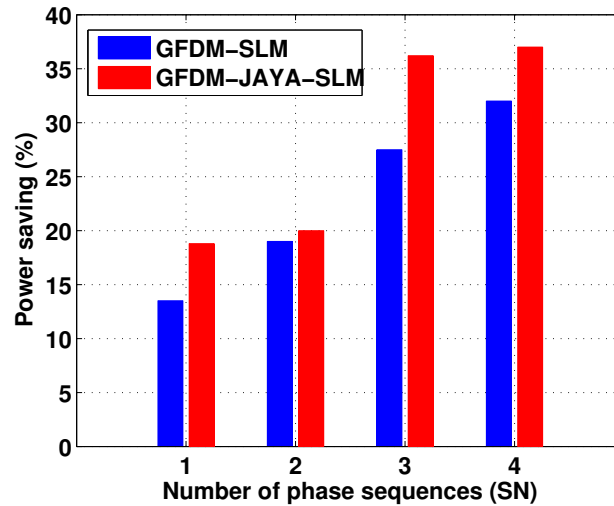


Figure 11. Impact of search number ($SN = 2, 4, 16, 64$) on the power saving in JAYA-SLM scheme with $K = 64$ subcarriers

Moreover, to further assess the efficiency of the suggested JAYA-SLM approach, the effect of varying the set size of subcarriers $K = \{64, 128, 256, 660\}$ is investigated while keeping the number of phase sequences fixed at $SN = 4$. The corresponding results are depicted in Figure 12. As highlighted in the following figure, the proposed method consistently achieves high power saving performance even as the number of subcarrier increases. For instance, at $K = 256$, the proposed technique attains a power saving of approximately 22.8%. These findings confirm the robustness of the proposed technique in maintaining power efficiency across different system configurations. In summary, the JAYA-SLM approach significantly enhances power saving, thereby ensuring its suitability for high-throughput wireless networks that operate with a large number of subcarriers.

5.4. The performance over the bit error rate

BER is an essential criterion for wireless networks, which reflects the effectiveness and reliability of transmitted data. It is defined as the ratio of the number of bit errors to the total number of bits transmitted. The BER is defined as (21):

$$BER = \frac{N_{er}}{N_t} \quad (21)$$

N_{er} and N_{total} denote the erroneous bits and total transmitted bits. In this context, the effectiveness of the suggested JAYA-SLM method is assessed based on the BER metric compared to the baseline GFDM framework. The

BER versus the SNR results are illustrated in Figure 13, for a configuration with $K = 128$ subcarriers and $SN = 2$ phase sequences. As depicted in this figure, the proposed technique attains at an $SNR = 15$ dB a BER of 10^{-6} , while the conventional GFDM system requires an SNR of 16 dB to reach the same BER level. This demonstrates that the proposed method provides improved reliability under comparable conditions.

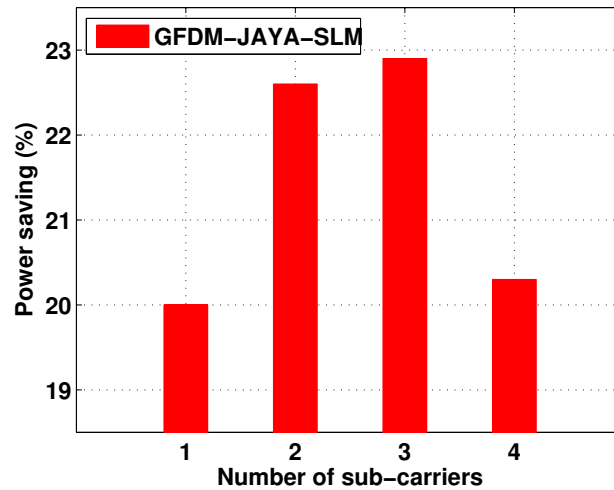


Figure 12. Impact of subcarrier count $K = 128, 256, 660$ on the power saving of JAYA-SLM with $SN = 4$

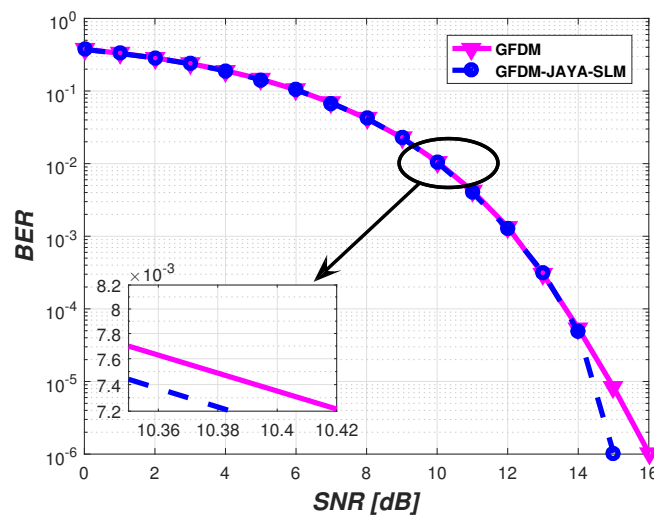


Figure 13. Comparison of BER between the GFDM system and GFDM-JAYA-SLM under identical modulation and transmission

5.5. Comparative analysis of JAYA-SLM with GA, PSO, and ABC

A comparative analysis was conducted to evaluate the performance of the proposed JAYA-SLM technique against conventional optimization algorithms, namely GA-SLM, PSO-SLM, and ABC-SLM. The comparison focused on convergence speed, computational complexity, and BER performance, as summarized in Table 4.

The convergence behavior of the considered algorithms was evaluated by monitoring the evolution of the objective function over successive iterations. The results demonstrate that JAYA-SLM converges as early as the second iteration, significantly outperforming GA-SLM, PSO-SLM, and ABC-SLM. This rapid convergence is mainly attributed to the parameter-free optimization strategy of the JAYA algorithm.

Table 4. Performance summary

Algorithm	Final fitness	Convergence iteration	Time/frame (s)	Complexity
JAYA-SLM	0.1187	2	430.5744	$O(I \times SN \times KM \log(KM))$
ABC-SLM	0.1380	22	1846.5739	$O(3 \cdot I \times SN \times KM \log(KM))$
PSO-SLM	0.1573	45	501.5032	$O(I \times SN \times KM \log(KM))$
GA-SLM	0.1482	41	174.3966	$O(I \times SN \times KM \log(KM) + SN^2)$

Compared with PSO-SLM, the proposed JAYA-SLM exhibits a more stable convergence behavior with reduced oscillatory fluctuations. Furthermore, unlike GA-SLM and PSO-SLM, JAYA-SLM does not require algorithm-specific control parameters such as crossover and mutation probabilities or velocity and position update coefficients. Consequently, the implementation complexity and computational overhead are considerably reduced.

It can also be observed that JAYA-SLM achieves the optimal phase factors within only two iterations, whereas ABC-SLM requires approximately 22 iterations to approach the optimal solution. This confirms the superior convergence capability and optimization efficiency of the proposed JAYA-SLM scheme.

The faster convergence of JAYA-SLM is further attributed to its directed update mechanism, in which each candidate solution is simultaneously guided toward the best solution while moving away from the worst solution in the population. This best-guided and worst-avoiding search strategy enhances exploitation capability and minimizes unnecessary random exploration during the optimization process. In contrast, ABC-SLM relies on probabilistic exploration mechanisms involving employed bees, onlooker bees, and scout bees, which increase the stochastic nature of the search process and consequently slow down convergence toward the optimal phase sequence.

6. DISCUSSION ON PRACTICAL DEPLOYMENT

While the simulation results demonstrate the effectiveness of the proposed JAYA-SLM approach for PAPR reduction in GFDM, several practical considerations remain for real-world deployment. For real-time implementation, the population-based nature of the JAYA algorithm allows parallel processing, making it suitable for FPGA or multicore architectures to satisfy latency constraints. Moreover, optimization can be performed periodically rather than on a per-frame basis to reduce computational overhead. Future hardware validation using platforms such as Xilinx Zynq or USRP SDRs is necessary to evaluate resource utilization, power consumption, and the impact of finite precision under realistic channel conditions. Furthermore, the proposed framework is inherently waveform-agnostic and can be extended to other multicarrier systems such as FBMC and UFMC by adapting the optimization process to account for filter bank structures and subcarrier overlap. Finally, the SI overhead, requiring $\log_2(M)$ bits per GFDM block, must be addressed. This can be mitigated using blind detection techniques or by embedding SI into reserved subcarriers to improve spectral efficiency. Addressing these challenges will bridge the gap between theoretical validation and practical transceiver implementation.

7. CONCLUSION

In various studies, the SLM technique has been widely recognized as an effective approach for PAPR mitigation. It is often employed in conjunction with optimization algorithms to identify optimal phase rotation factors. However, many of these combined methods introduce considerable computational complexity due to the reliance on numerous control parameters. To overcome this limitation, this work proposes an enhanced SLM scheme, termed JAYA-SLM, which integrates the SLM technique with the simple yet powerful JAYA optimization algorithm. The proposed approach relies on the JAYA algorithm to optimize the phase sequence selection without requiring any control parameter tuning, which simplifies the implementation and reduces computational complexity while ensuring efficient convergence. The proposed method achieves a significant PAPR reduction of approximately 30% on average across different scenarios, with improvements reaching up to 42% under specific simulation conditions, without increasing system complexity. In addition to its efficient PAPR performance, the JAYA-SLM approach maintains an acceptable BER under different SNR conditions and demonstrates notable power-saving capabilities. Furthermore, comparative results confirm that the proposed method provides superior performance in terms of PAPR reduction, BER, and computational simplicity when compared with conventional GFDM-based SLM schemes as well as optimization-based approaches such as ABC, GA, BBO, and other low-complexity SLM techniques. Owing to its scalability and low overhead, the proposed technique is well-suited for large-scale GFDM deployments and is particularly appropriate for next-generation wireless systems. The proposed method improves energy efficiency and is suitable for real-time 5G/IoT systems.

As part of future work, the proposed scheme can be extended toward hardware implementation to evaluate its real-time feasibility and computational efficiency. Furthermore, the investigation of adaptive or hybrid variants of the JAYA algorithm is expected to further enhance optimization performance under dynamic conditions. Additionally, extending the proposed approach to other advanced multicarrier waveforms represents a promising direction for broadening its applicability.

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Fo	: Formal Analysis	E	: Writing - Review & Editing		

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request.

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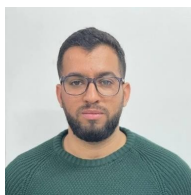
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