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Original Article

An Improved Hybrid GA-PSO-Based PTS Scheme for PAPR Reduction in OFDM Systems

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Abstract - *Orthogonal Frequency Division Multiplexing (OFDM) has become one of the most widely used modern wireless communications as a result of its inherent capabilities of efficiently utilizing spectrum and resisting multipath fading. High Peak-to-Average Power Ration (PAPR) is one of the significant challenges of OFDM systems, resulting in power efficiency reduction and signal quality degradation. This paper presents an enhanced Partial Transmit Sequence (PTS) technique that leverages a hybrid Genetic Algorithm–Particle Swarm Optimization (GA-PSO) to lower PAPR while keeping computational demands low effectively. By combining the broad exploration capability of GA with the fast convergence of PSO, the hybrid method efficiently identifies optimal phase factors. MATLAB simulations with 10,000 OFDM frames and 16-QAM modulation show that the GA-PSO approach achieves PAPR reduction comparable to conventional PTS, outperforming GA-PTS and PSO-PTS alone. The method reached a PAPR of 5.16 dB at a CCDF of 10^{-4} with only 1200 iterations, demonstrating its practicality and efficiency for OFDM systems.*

Keywords - *Genetic Algorithm, Orthogonal Frequency Division Multiplexing, Partial Transmit Sequence, Peak to Average Power Ratio, Particle Swarm Optimization.*

1. Introduction

The demand for high-speed data transmissions has increased tremendously [1] with the development of high data rate wireless systems like 4G, 5G, and beyond. Orthogonal Frequency Division Multiplexing is a well-known multicarrier system that offers high data rates, high spectral efficiency, and robustness against multipath fading [1]. OFDM has been widely adopted in wireless standards [2], including 4G and 5G, among others. It allows the transmission of multiple data streams simultaneously on separate orthogonal carriers using the Inverse Fast Fourier Transform at the transmitter side and the Fast Fourier transform at the receiver side [3].

Nevertheless, one of the biggest drawbacks of OFDM systems is the High Peak to Average Power Ratio in their waveform [4]. High PAPR leads to power consumption and signal distortion, compromising the quality of the transmission. To mitigate the high PAPR inherent in OFDM systems, many methods have been proposed, including Clipping and Filtering [5], Compounding [6], Tone Injection, Selective Mapping [7], and Partial Transmit Sequence [8]. Partial Transmit Sequence emerges as one of the preferred methods for its performance in reducing the PAPR without increasing the Bit Error Rate (BER) [1]. The PTS method initially divides the input data into disjoint blocks, applies the IFFT to each subblock, then multiplies each of them by a phase rotating factor, and finally selects the combination with the lowest PAPR for transmission. The exhaustive search for the optimal phase factor increases exponentially as the number of subblocks grows.

However, the exponential search complexity remains a major limitation that affects the real-time implementation of PTS. Despite several optimization techniques proposed to simplify the phase factor search, most existing solutions still face a trade-off between performance and computational cost. Several researchers have proposed modified versions of PTS to overcome its high search complexity. A few recent and relevant studies are outlined below.

In 2022, Yuan et al. proposed an Adaptive PTS based on a Fuzzy Neural Network [9]. The proposed FNN-PTS combined FNN and PTS to adaptively select the number of subblocks according to the power of the input signal.

Aghdam and Sharifi [10] proposed an enhanced PTS method using PSO to address the computational complexity at the phase factor search. The PSO algorithm achieved lower computational complexity, but this came at the expense of some degradation in PAPR reduction performance.

Somia et al. [11] proposed a hybrid IF-PSO-based PTS by combining Iterative Flipping and Particle Swarm Optimization. The proposed IF-PSO method enhanced the initial solution from the IF algorithm and improved it with PSO, allowing for better diversity and exploration. While the method reduced the computational complexity of the PTS, it impacted the PAPR performance.

Another method was proposed by Xue et al. [3]in 2023. The authors introduced an optimized PTS using the Chaotic Biogeographical-based Optimization (CBBO) algorithm. This method leveraged the Hermitian symmetry property to yield real-valued time-domain signals and combined phase rotation factor optimization with chaotic mechanisms to enhance convergence speed and reduce complexity compared to traditional methods.

An ABC-PTS was proposed by Wang et al. using the Artificial Bee Colony Algorithm [12]. In their approach, a three-step process was used for the phase factor search. It involved employing bees, onlookers, and scouts to explore and exploit potential solutions.

A hybrid SCA-GWO was proposed by Somia et al. in [13]. In their method, they leveraged SCA for initial global solution exploration and GWO for enhanced convergence.

Joo et al. [2] proposed a PTS-free side information by relying on intelligent signal manipulation to allow the receiver to recover the original data without extra information.

Zeid et al. proposed PTS with combined partitioning [14]. In their method, the authors combined adjacent and interleaved partitioning schemes. They introduced a hybrid method that constructs blocked interleaved partitions for more effective phase factor optimization.

Hongmei et al. [8] proposed a Multiple discrete particle swarm for phase factor search in PTS. The MDPSO approach enhanced efficiency by using dynamic, time-varying learning factors to prevent premature convergence in DPSO. MDPSO-PTS outperformed standard DPSO-PTS in PAPR reduction while maintaining lower complexity than traditional PTS methods.

A modified PTS with a Non-Uniform Phase factor was proposed by Tsai and Huang [15]. In order to solve the computational complexity of the PTS at the phase factor search, this research proposes a hybrid phase optimisation approach that combines Particle Swarm Optimisation and Genetic Algorithm. The proposed method leverages the strength of both algorithms to optimize the phase factor search in PTS.

Despite these advances, a consistent balance between reduction performance and computational efficiency remains unresolved. Most techniques either reduce complexity at the cost of PAPR performance or achieve a strong reduction with heavy computation. This trade-off forms the central gap addressed in this work.

The proposed hybrid GA-PSO-based PTS combines the broad search capability of GA with the rapid convergence of PSO to achieve efficient and reliable PAPR reduction suitable for practical OFDM systems. The rest of this paper is organised as follows: In Section 2, the system model is described, the methodology is presented in Section 3, the results are presented in Section 4, and the conclusion is in Section 5.

2. System Model

2.1. OFDM System Model

In OFDM, the available frequency spectrum is divided into multiple orthogonal subcarriers, each carrying a portion of the total data payload. Given the number of subcarriers as N, the frequency domain can be represented as, $X = [X_1, X_2, \dots, X_{N-1}]$, consequently, the time domain signal is obtained by performing an IFFT and can be represented by $x = [x_1, x_2, \dots, x_{N-1}]$.

$$x_n = \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} X_k e^{j\frac{2\pi}{N}kn}, 0 \le n \le N-1 \qquad (1)$$

Here, X_k denotes the signal in the frequency domain obtained after subcarrier modulation. Figure 1 presents the block diagram of a typical OFDM system.

2.2. PAPR and CCDF

The PAPR of the OFDM signal x_n is defined as the ratio of the maximum power to the average and can be obtained by

$$\text{PAPR} = \frac{\max\{|x_n|^2\}}{E\{|x_n|^2\}}, \quad 0 \le n \le N-1 \qquad (2)$$

The complementary cumulative distribution function is a statistical function used to analyze the Peak to Average Power Ratio. It is the probability that the signal exceeds a given threshold and helps us measure how well the method does.

$$CCDF = \Pr(PAPPR > PAPR_0) \\ = 1 - (1 - exp(PAPR0))^{N.L} \qquad (3)$$

Where $PAPR_0$ is the threshold power.

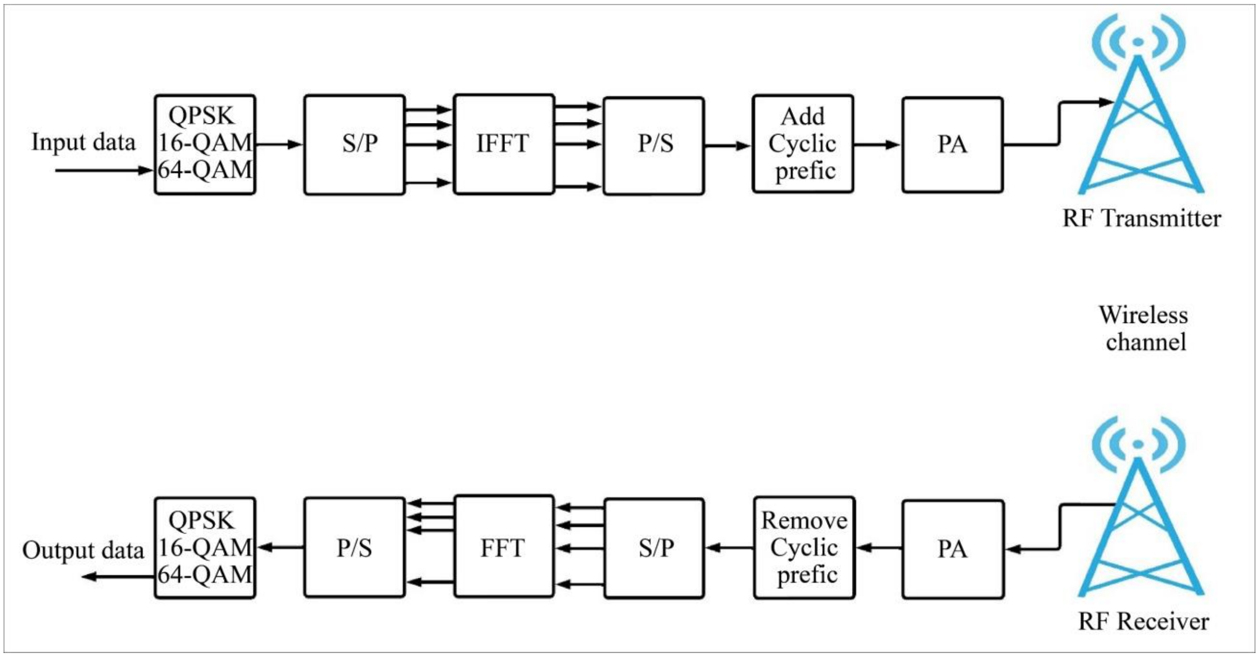


Fig. 1 Functional decomposition of the OFDM system

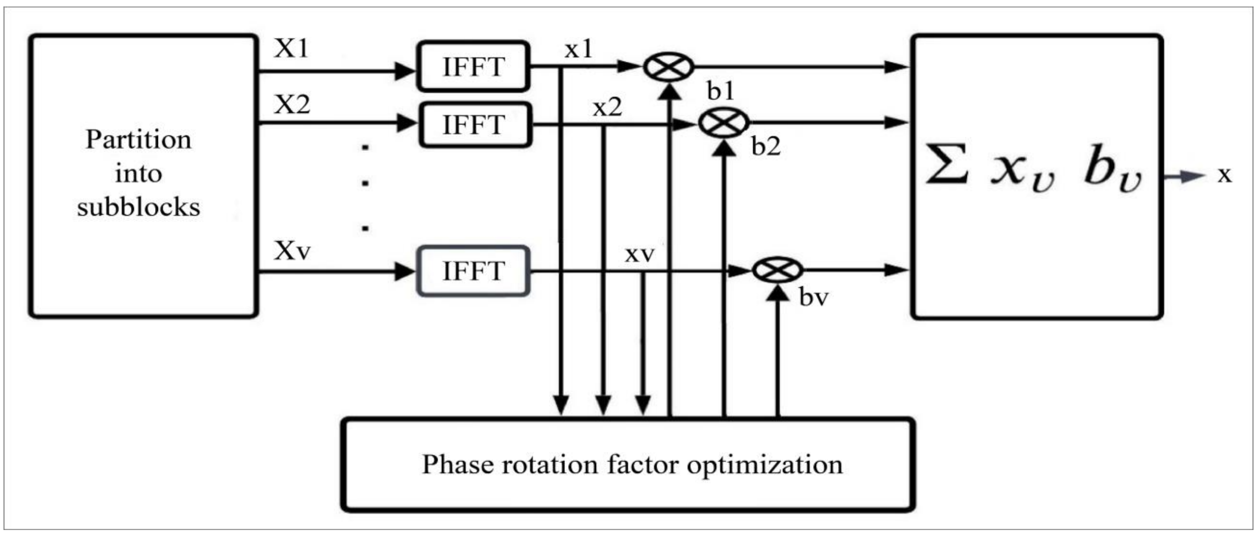


Fig. 2 Functional decomposition of PTS

2.3. Partial Transmit Sequence

Partial transmit sequence is a method used to reduce the PAPR in OFDM systems. First, the frequency domain signal X is divided into V disjoint blocks, and then the IFFT is performed to transform the signal into the time domain. After the IFFT process, each subblock is multiplied by a phase-rotating factor. Finally, the signal is recombined by adding the blocks together. The phase combination with the smallest PAPR is chosen for transmission. Figure 2 shows the block diagram of the PTS scheme, which can be expressed as Equation 4:

$$x = \sum_{v=1}^{V} b_v x_v \ = \sum_{v=1}^{V} b_v IFFT\{X_v\} \quad (4)$$

Where $b_v = e^{j\varphi_v}$, with $\varphi_v = [0, 2\pi]$, $1 \le v \le V$

The choice of phase factors is expressed as

$$[\tilde{b}_1, \tilde{b}_2, \dots, \tilde{b}_v] = {}^{argmin\,\{\max|\sum_{v=1}^{V} b_v x^v|\}}_{[b_1, b_2, \dots, b_v]} \quad (5)$$

Although PTS has the ability to reduce the PAPR in OFDM systems efficiently, its computational complexity at the phase factor search makes it inefficient for a large number of subblocks. The phase factor search complexity grows exponentially with the number of sub-blocks. To overcome the complexity of the exhaustive search of the conventional PTS method, this paper presents a hybrid GA-PSO for the phase factor search.

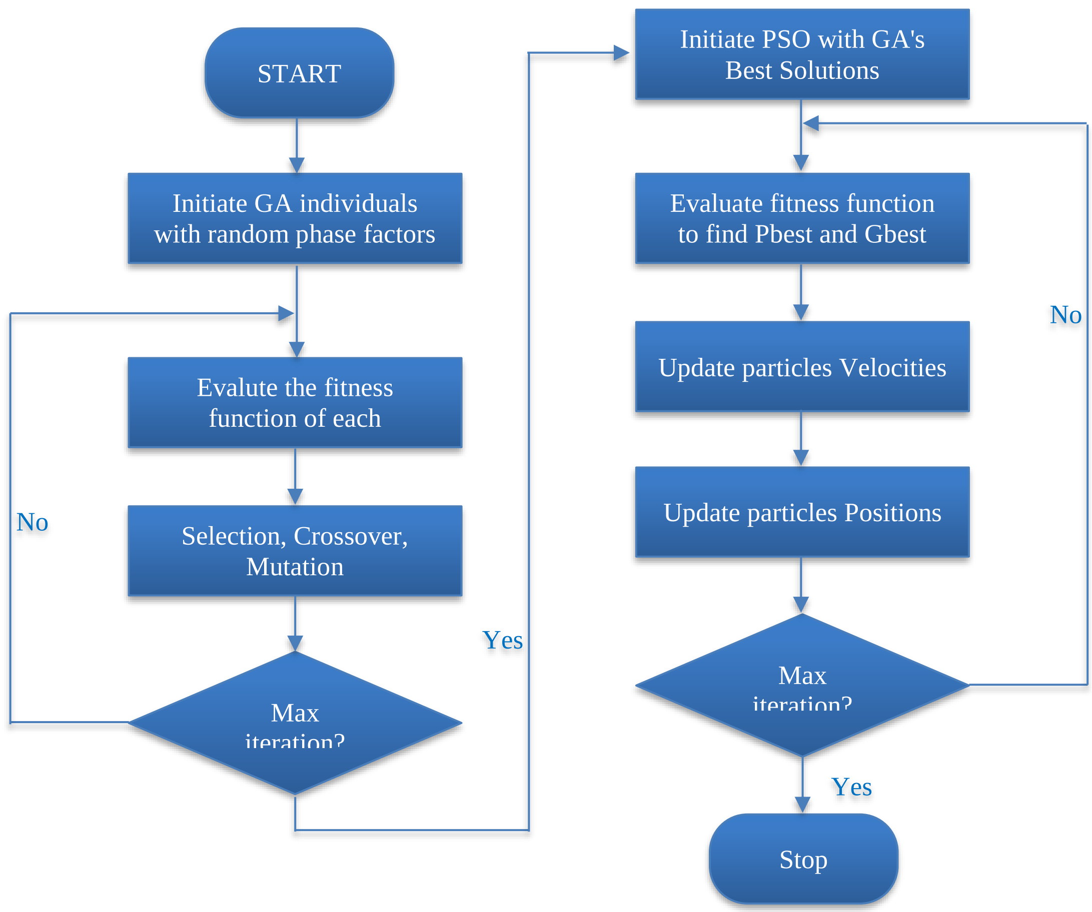


Fig. 3 Flowchart of the hybrid GA-PSO

3. Proposed Method

In this paper, a hybrid GA-PSO is introduced to reduce the computational complexity of the PTS method. In PTS, the phase factor search grows exponentially with the increase in sub-blocks. To overcome the computational complexity related to the phase factor search, a hybrid GA-PSO for optimal phase search was proposed. This approach combines the exploration capabilities of GA with the exploitation abilities of PSO, leading to better optimization performance.

The Genetic algorithm, as introduced by John Holland in 1975 [16-18], applies principles derived from biological evolution, notably the concepts of natural selection, to solve optimization problems.

Each individual in the population is represented by a set of phase factor:$b = [b_{1,}b_2, \dots, b_m]$. The dimension of the individual represents the number of sub-blocks in the PTS method, and each. b_i It is a phase factor selected from a predefined set. $b_i \epsilon$ {1,-1,j,-j}

First, all the individuals in the population are initialized with a random phase factor, then the fitness function of each individual is calculated using the formula fitness(b) = PAPR(x(b)).

The individuals with lower PAPR are used for creating the next generation. Then, individuals with the best fitness values corresponding to lower PAPR are selected to create offspring. Finally, a mutation is introduced, altering some of the factors randomly to maintain genetic diversity in the population. Then the process is repeated for the number of iterations. After convergence, the best solutions are passed to PSO for further processing.

Particle swarm optimization is a computational method inspired by the social behavior of birds and fish. Developed by Russel Eberhart and James Kennedy in 1995 [10, 19, 20], PSO is used to solve optimization problems by simulating the social behavior of fish and birds (representing potential solutions) as they navigate through the solution space.

In this approach, PSO is initialized by the best solutions derived from GA. Each selected individual from the GA becomes a particle in the PSO framework. Initial velocities v_i are assigned randomly to each particle, and the personal best $pbest_i$ The mass of each particle is computed.

The fitness of each particle is evaluated by computing the PAPR associated with the phase factor combination represented by its position. As the particles move through the solution space, their positions are updated according to their velocity and the influences of both their individual best and the global best in the entire swarm. The particles' positions and velocities are updated according to equations (6) and (7).

$$v_i(t+1) = w \cdot v_i(t) + c_1 r_1(\mathrm{pbest} - \mathrm{p}_i(\mathrm{t}) + c_2 r_2\big(gbest - \mathrm{p}_i(t)\big) \quad (6)$$

$$\mathrm{P}_i(t+1) = \mathrm{p}_i(t) + v_i(t+1) \quad (7)$$

Where:

$v_i(t)$ and $\mathrm{p}_i(\mathrm{t})$ are particle i velocity and position, respectively.

w is the inertia weight, which controls the impact of

The previous velocity is compared to the current one.

c_1 and c_2 are cognitive and social coefficients, respectively, that have an influence on the personal and global best positions.

r_1 and r_2 are random numbers uniformly distributed in the range [0, 1].

After updating the positions, the PAPR of each particle is computed again to evaluate its fitness and to update the personal and global best values. Through optimization, each particle maintains a record of its personal best position $pbest_i$, which corresponds to the phase factor combination that produced the lowest PAPR observed so far by the particle.

The global best (gbest) position is updated to reflect the best-performing phase factor combination found among all particles in the swarm. The PSO converges toward the global best, corresponding to the optimal combination of phase factor with the lowest PAPR.

Algorithm Hybrid GA-PSO

```
Initialize parameters, GA individuals with random
phase factors, t_max
    for each individual b_i do
      Calculate fitness(b_i)= PAPR(x_i)
    end for
    while t < t_max
(t_max is the number of iterations)
    Select individuals with the best fitness for
formatting
    Create offspring using crossover and mutation
       for each individual b_i do
            Calculate fitness(b_i) = PAPR(x_i)
       end for
       Replace the worst individuals with new
offspring
    end while
    Initialize PSO particles with the best solutions
from GA
    for each particle p_i do
      set initial velocity v_i randomly
      calculate personal best, pbest_i and global best
gbest_i
    end for
    while t < t_max
      For each particle p_i do
          Update velocity and position using equations
(6) and (7)
          Evaluate fitness(p_i) = PAPR(x)
          if fitness(p_i) < fitness( pbest_i) then
              Update personal best: ( pbest_i =p_i
          end if
          if fitness(p_i)<fitness(( gbest_i) then
          Update global best: gbest_i=p_i
          end if
       end for
    end while
    return gbest as the optimal phase factor
```

The complexity of the proposed method is computed by multiplying the population size P by the number of iterations I. The population size used in this paper is 30 for both Ga and PSO, and the iterations are 20

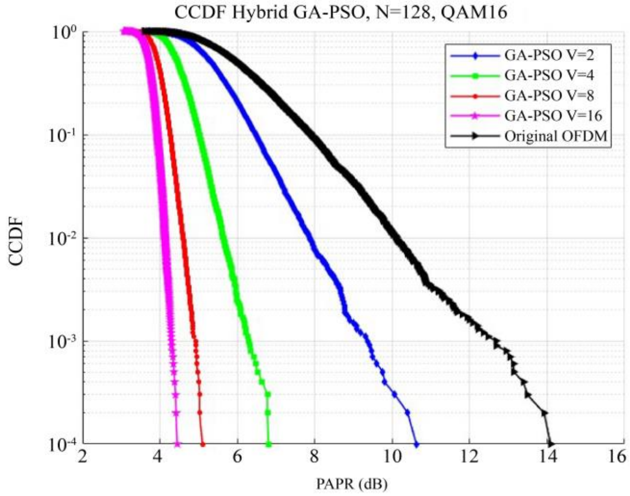
4. Results and Discussions

The simulations were conducted in MATLAB R2023a over 10,000 OFDM frames using 16-QAM modulation. A set of four phase factors $\{1, -1, j, -j\}$ was used. Table 1 gives a summary of the simulation parameters. These choices provide a balance between practical implementation and computational feasibility in evaluating the PAPR reduction performance.

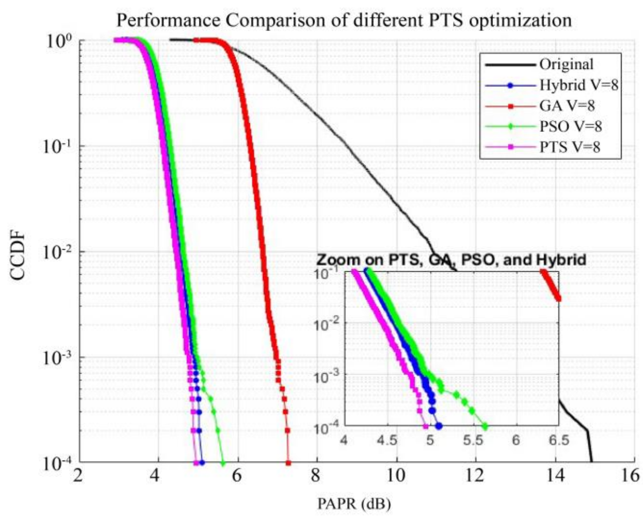
Table 1. Simulation parameters

Parameters	
Oversampling factor	4
Modulation	16-QAM
Number of OFDM blocks	10000
Number of subcarriers	128,256
Mutation	0.01
Crossover	Single point
Number of iterations	20
C1	1.5
C2	0.5
Number of carriers	256
Population size	30
Number of allowed phase factors	4

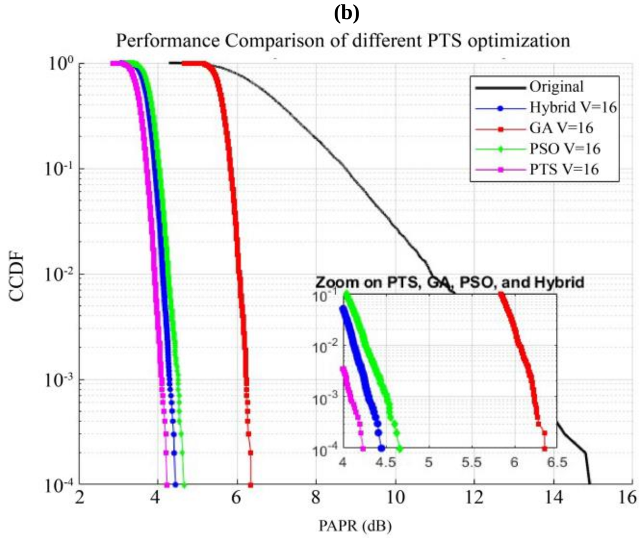
4.1. PAPR Performances



(a)

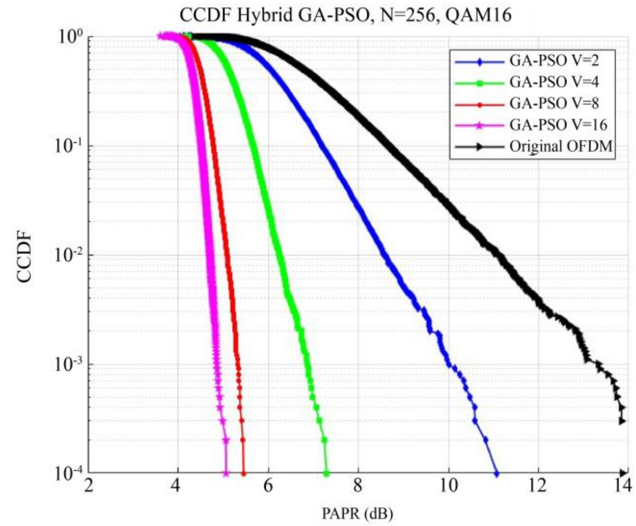


(b)

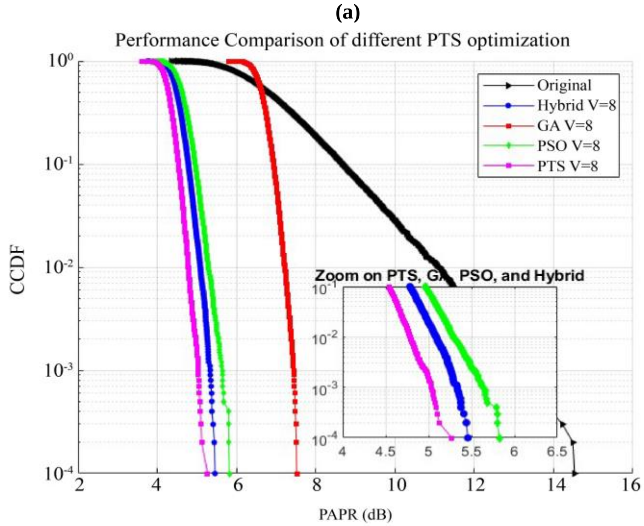


(c)

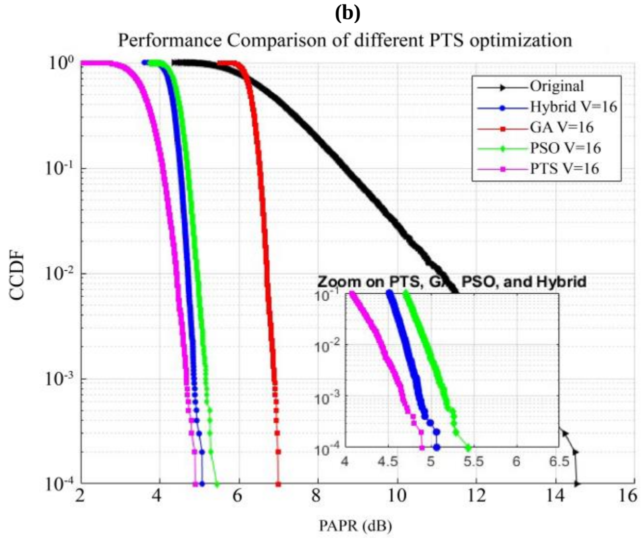
Fig. 4 CCDF vs PAPR, N=128, (a) Hybrid GA-PSO-PTS, (b) and (c) Performance comparison of PTS optimization methods V=8, and V=16, respectively.



(a)



(b)



(c)

Fig. 5 CCDF vs PAPR, N=256, (a) Hybrid GA-PSO-PTS, (b) and (c) Performance comparison of PTS optimization methods V=8, and V=16, respectively.

Figures 4 and 5 show how the number of subcarriers and subblocks affects the PAPR reduction performance of Different methods. These figures assist in understanding the performance of each technique under different settings.

Figures 4(a) and 5(a) illustrate the CCDF comparison of the hybrid GA-PSO method against the original OFDM signal for different subblocks with *N* equal 128 and 256 subcarriers respectively. The hybrid technique considerably reduces the PAPR, as shown in these figures.

A comparison between the performance of different optimization-based PTS for *V*=8 and *N* equal 128 and 256 is shown in Figures 4(b) and 5(b). The hybrid GA-PSO clearly outperforms standalone GA and PSO in PAPR reduction, achieving a better balance between performance and complexity.

Furthermore, Figures 4(c) and 5(b) extend the comparison to *V*=16, highlighting how the hybrid method maintains strong performance with increased subblocks. Table 2 provides a detailed comparison of PAPR values for *N*=128 and *N*=256 at CCDF of 10^{-4}.

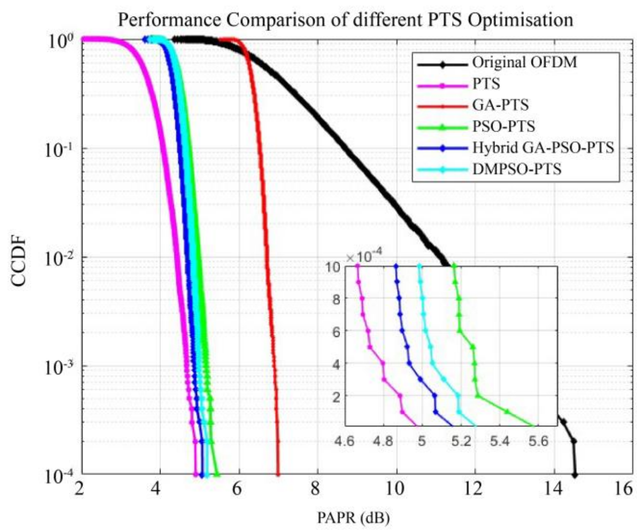


Fig. 6 CCDF vs PAPR, N=256: Performance comparison of PTS Optimization Methods V=16

Table 2. Performances comparison of PTS optimization methods at CCDF of 10^{-4}

PTS Optimization method	CCDF			
	N=128		N=256	
	V=8	V=16	V=8	V=16
GA-PTS	7.26	6.49	7.62	7.02
PSO-PTS	5.4	4.7	5.68	5.59
GA-PSO-PTS	5.03	4.49	5.61	5.16
PTS	5.15	4.28	5.33	4.48

The hybrid GA-PSO-PTS achieves better results than existing optimization-based PTS methods because it exploits the complementary strengths of both algorithms. In the GA phase, population diversity is maintained through crossover and mutation, which prevents premature convergence and ensures a broad exploration of the phase-factor search space. These diverse and near-optimal candidates are then passed to the PSO stage, where swarm interactions refine the solutions efficiently toward the global optimum. This two-level search mechanism minimizes the likelihood of local stagnation and yields phase combinations that produce lower PAPR values.

Compared with the MDPSO-PTS (Figure 6) reported by Hongmei et al. (2024), which achieved a PAPR of 5.28 dB at a CCDF of 10^{-4}, the proposed hybrid GA-PSO obtained 5.16 dB under the same conditions. The gain is attributed to GA's robust global search and PSO's rapid local convergence, which together enhance both accuracy and stability. Additionally, the hybrid method maintains the same computational cost as individual GA or PSO runs because it reuses GA-generated populations within PSO iterations rather than expanding them. Consequently, the approach achieves near-optimal PAPR reduction at a fraction of the complexity of conventional PTS, demonstrating that a cooperative hybrid design can overcome the performance-complexity trade-off observed in prior work.

4.2. Computational Complexity

Table 3 shows the computational complexity for the different PTS optimization methods in terms of the number of complex multiplications at *V*=16. The conventional PTS method uses an exhaustive search over all possible phase combinations, which results in a very high complexity, especially when the number of subblocks increases. For example, with 16 subblocks and a phase factor set of size 4, the complexity becomes 4^{16}=4,294,967,2964 complex multiplications. This is extremely large and becomes impractical for *V*>16.

On the other hand, all three metaheuristic methods, GA, PSO, and the proposed hybrid GA-PSO, only require 1,200 complex multiplications. The hybrid method combines the strengths of GA and PSO while maintaining the same level of complexity as the individual techniques. This means the hybrid GA-PSO method reduces the computational burden by a factor of approximately 3.58 million times compared to conventional PTS at *V*=16, while still achieving competitive PAPR reduction performance. This makes it a much more practical solution for modern OFDM systems.

Table 3. Computational complexity analysis at V=16

Method	Computational complexity (Complex multiplications)
GA-PSO	(I*P) + (I*P) = 20*30+20*30= 1200
PSO	I*P = 40*30 = 1200
GA	I*P = 40*30 = 1200
PTS	$W^V = 4^{16}$ = 4,294964296

5. Conclusion

This paper proposed an improved PTS scheme using a hybrid GA-PSO approach to reduce the PAPR in OFDM systems. The hybrid method was evaluated against conventional PTS, GA-PTS, and PSO-PTS for subblock sizes 8 and 16 with a number of subcarriers of 128 and 256. Simulation results demonstrated that the GA-PSO approach consistently outperformed standalone GA and PSO methods, achieving PAPR reductions of 5.61 dB and 5.16 dB, respectively, at *N*=256, with a fixed computational cost of 1,200 iterations. While the conventional PTS method offered slightly better PAPR performance (5.33dB and 4.98 dB, respectively, at *V*=8 and *V*=16), its exponentially increasing complexity renders it impractical for a number of subblocks greater than 16.The hybrid GA-PSO offers a scalable and efficient approach that provides near-optimal performance at a fraction of the computational cost of the conventional PTS.

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