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Improved Algorithm of Partial Transmit Sequence Based on Discrete Particle Swarm Optimization

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Abstract: Orthogonal frequency division multiplexing (OFDM) in 5G has many advantages; however, one of the disadvantages is that the superposition of a large number of subcarriers leads to a high peak-to-average power ratio (PAPR) of the transmit signal. A high PAPR results in high-power amplifier distortion and performance degradation. The partial transmit sequence (PTS) algorithm is commonly used for PAPR reduction. It enumerates all combinations of phase factors, weighs the signal using each phase factor combination, and finds the set of phase factors that minimizes the PAPR value of the OFDM signal. The advantage of the PTS is that it determines the optimal solution through enumeration; however, its major drawback is the higher complexity caused by the use of enumeration. Some studies have introduced the discrete particle swarm optimization (DPSO) algorithm instead of enumeration to determine the optimal solution of the PTS algorithm. As an excellent optimization method, the DPSO algorithm represents each individual as a solution during the optimization. Through iterative updates of the initial population, individuals in the population continuously move closer to the optimal solution. This approach significantly reduces complexity compared with the exhaustive enumeration used in the traditional PTS algorithm. However, the disadvantage of the general DPSO algorithm is that it can result in premature and early convergence, which leads to degradation of the PAPR reduction performance. In this study, we propose an improved method based on the general DPSO-based PTS algorithm, and the improved algorithm MDPSO-PTS adopts dynamic time-varying learning factors, which can find the optimal combination of phase factors more efficiently. The MDPSO-PTS algorithm expands the search space when seeking the optimal combination of phase factors. This avoids the drawback of premature convergence commonly observed in general DPSO-PTS algorithms, preventing early consideration of local optima as global optima. A comparative simulation of the improved MDPSO-PTS algorithm with the general DPSO-PTS algorithm shows that the improved algorithm has stronger PAPR reduction, whereas the complexity remains basically unchanged. A comparative simulation with the traditional PTS algorithm shows a significant reduction in complexity, with only a slight, acceptable loss of reduction performance.

Keywords: orthogonal frequency division multiplexing (OFDM); peak-to-average power ratio suppression (PAPR); partial transmit sequence (PTS); discrete particle swarm optimization (DPSO)

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1. Introduction

Orthogonal frequency division multiplexing (OFDM) is one of the core technologies of the physical layer in 5G New Radio (5GNR). OFDM possesses the advantages of a high transmission rate and strong resistance to multipath interference and can be combined with large-scale MIMO [1,2]. OFDM, as a multicarrier modulation technique, has been chosen as the downlink waveform for 5G communication systems [3], and it is widely used. OFDM technology possesses many advantages, but its disadvantage is that a high peak-to-average power ratio (PAPR) seriously affects the system performance, leading to the distortion of OFDM signals in the nonlinear region of the high-power amplifier (HPA). Conversely, the probability of the occurrence of a high PAPR in OFDM signals is low, and expanding the linear operating range of the HPA in a single step reduces its efficiency [4]. However, owing to the limited range of device standards, the linear region range of the HPA is also limited. Therefore, it is significant to investigate the reduction of the PAPR of signals in OFDM systems.

PAPR reduction techniques have been extensively studied in the following three main categories:

(1) Signal-predistortion class techniques

Clipping and compression expansion techniques are the main signal predistortion techniques [5–7]. The clipping technique reduces the PAPR of an OFDM signal by cutting off the signal amplitudes above a threshold value, thereby reducing the amplitude of the peak signals. The principle of the compression-expansion technique is to compress the amplitudes of large signals while expanding the amplitudes of small signals, thereby ensuring a constant average power to reduce the PAPR. The biggest advantage of this type of PAPR reduction method is that it is simple to implement, and the PAPR reduction effect is significant. The disadvantage is that this technique is a nonlinear transformation, and the nonlinear operation of the signal produces a nonlinear distortion. This can affect the bit error rate (BER) and performance of the entire communication system;

(2) Coding class technique

The coding-class technique selects a specific code word to encode a bit stream. Commonly used code words include group codes [8] and Gray's complementary codes [9,10]. The codewords used for coding have lower-amplitude peaks, and the coded bit stream has lower PAPR values. The coding class technique, as a linear transformation class method, has the advantage of not increasing signal distortion. One disadvantage is that redundant information must be transmitted during coding, which reduces the transmission efficiency of the system;

(3) Probabilistic class techniques

Probabilistic class techniques are linear transformations that not only do not result in an increase in the BER but also have good PAPR reduction performance. This class of technology is widely applied with a focus on reducing the probability of peak occurrences. The most commonly used probabilistic class techniques are the Partial Transmit Sequence (PTS) method [7–13] and Selective Mapping (SLM) algorithm [14–18]. The disadvantage of the probabilistic class technique is that its computational complexity is high, requiring multiple inverse fast Fourier transform (IFFT) operations and calculation of the PAPR. Researchers have introduced optimization algorithms into the PTS to reduce its complexity. For a PTS-OFDM system, the authors in [19–21] proposed an artificial bee colony algorithm, differential evolution search, and genetic algorithms, respectively. These algorithms have limitations in terms of the convergence speed and PAPR reduction capability.

The algorithm used in this study is based on the PTS algorithm, which is an effective and distortion-free PAPR reduction method. The traditional PTS algorithm is based on exhausting all phase factor combinations and finding the phase factor that minimizes the PAPR of the OFDM symbols. The high complexity of the PTS algorithm lies in determining the optimal phase factor. To address the limitations of the PTS algorithm, researchers in [9] introduced the discrete particle swarm optimization (DPSO) algorithm into the PTS algorithm, resulting in improved PAPR reduction effectiveness. The DPSO algorithm is a group intelligence algorithm that is simple to implement and highly efficient. In the DPSO algorithm used to determine the optimal phase factor, each individual represents a combination of phase factors. By continuously updating each individual in the population, individuals move towards the optimal solution, ultimately converging the entire population near the optimal solution. This optimization process replaces the exhaustive enumeration procedure in the traditional PTS, which can be a suitable solution to the problem of high computational complexity owing to searching for the phase factor in the PTS algorithm [14,15]. However, conventional DPSO algorithms often experience premature convergence, becoming trapped in local optima, and mistakenly considering them as global optima. This premature convergence leads to a false optimal solution and results in the degradation of the PAPR reduction performance. Therefore, in this paper, an improved PTS algorithm based on DPSO is proposed. The improved MDPSO-PTS algorithm incorporates dynamic and time-varying learning factors, which help avoid premature convergence and prevent the algorithm from becoming trapped in local optima. By enlarging the search space, the algorithm aims to determine the phase factor combination that results in a lower PAPR value. The conclusions drawn from the simulation experiments indicate that the proposed MDPSO-PTS algorithm exhibits superior PAPR reduction performance compared with the conventional DPSO-PTS algorithm without dynamic learning factors. Moreover, compared with the traditional PTS algorithm, the proposed algorithm achieves a significant reduction of computational complexity while incurring minimal performance loss. A reduction of complexity can reduce the transmission latency of OFDM communication systems, lower hardware requirements, reduce costs, and enhance communication quality.

The remainder of this paper is organized as follows. Section 2 describes the basic principles of OFDM and the PAPR problem. Section 3 describes the concept of the PTS algorithm based on the DPSO and the MDPSO-PTS improvement method. Section 4 compares and analyzes the traditional and improved algorithms using MATLAB simulation experiments. Section 5 summarizes the advantages of the MDPSO-PTS algorithm, explains the importance of the PAPR-reduction algorithm in OFDM technology, and highlights future research directions.

2. OFDM Fundamentals and the Peak-to-Average Ratio Problem

OFDM is an efficient digital communication technique widely used in modern wireless communication systems. It modulates the bit stream on multiple noninterfering subcarriers to increase the data transmission rate and system capacity, and strict orthogonality is required between the subcarriers. Figure 1 shows a basic modulation block diagram of OFDM.

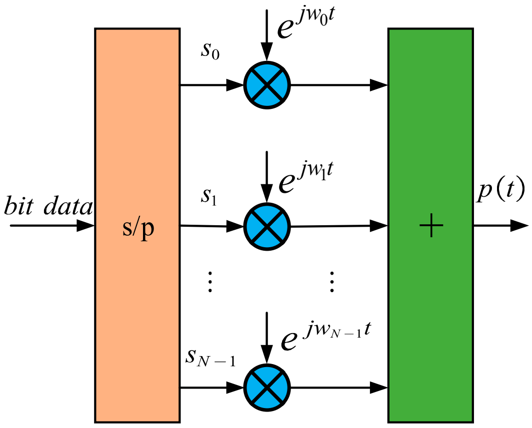

Figure 1. Basic modulation block diagram of OFDM.

On the transmitter side, the source first transmits serial bit data, which are converted into a parallel stream after constellation mapping and serial-to-parallel conversion. Each symbol is placed on an orthogonal subcarrier and superimposed to obtain the time domain signal to be transmitted. The process of modulating each frequency domain signal onto orthogonal subcarriers and superimposing them is equivalent to the inverse fast Fourier transform (IFFT), which is generally referred to as the IFFT. After the channel transmission, the original data can be recovered by performing an inverse operation on the received signal at the receiving end.

For OFDM systems, due to the use of multiple carriers to transmit data in parallel, a higher PAPR can lead to the distortion of nonlinear components in the system, such as power amplifiers, thus degrading the performance of the system [7]. Assuming that the frequency domain data after constellation mapping is $X(k)$, $X(k)$ passes through the IFFT block and generates the baseband signal. The n^{th} sample of the OFDM signal can be expressed by Equation (1):

$$x_n = \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} X_k \cdot \exp\left(j\frac{2\pi}{N}kn\right), 0 \leq n \leq N-1, \tag{1}$$

The PAPR of an OFDM signal is the ratio of the maximum power to the average power [22], which can be expressed by Equation (2):

$$\text{PAPR} = \frac{\max\left\{|x_n|^2\right\}}{\text{E}\left\{|x_n|^2\right\}}, \tag{2}$$

where $x(n)$ denotes the time domain symbols that have been transformed by the IFFT, and the OFDM signal has a high PAPR. The complementary cumulative distribution function (CCDF) is used to measure the magnitude of the PAPR, which indicates the probability that the signal was greater than a certain threshold value. This is expressed in Equation (3).

$$\text{CCDF} = P(\text{PAPR} > \text{PAPR}_0) = 1 - \left(1 - e^{-\text{PAPR}_0}\right)^N, \tag{3}$$

In this study, the PTS algorithm, a probabilistic class technique, is used. The PTS algorithm has been widely used and researched because of its excellent PAPR reduction performance [23]. The PTS algorithm is less complex and easier to implement than other probabilistic class SLM algorithms. As shown in Figure 2, in OFDM modulation, the core idea of the PTS algorithm is to divide the OFDM frequency domain sequence into multiple sub-blocks. Each sub-block is then weighted with different combinations of phase factors, and the optimal combination of phase factors is selected to reduce the PAPR of the entire OFDM time domain signal [13]. In the specific realization process, a signal X of length N is first divided into V subblocks, and the grouped data are expressed as $X = [X_1, X_2, \cdots, X_v]$. Assume a phase space p containing M phase factors, $p = \left\{e^{j2\pi w/M} \mid w \in [0, M-1]\right\}$. Each sub-block of the grouped signal selects a phase factor to be multiplied by, and the combination of phase factors selected for the V sub-block data is $p_v(v = 1, 2, \ldots, V)$. Finally, the data are transformed to the time domain using the IFFT to obtain the transmitter signal, as shown in Equation (4):

$$x = \text{IFFT}\left\{\sum_{v=1}^{v} p_v X_v\right\} = \sum_{v=1}^{v} p_v \cdot \text{IFFT}\{X_v\} = \sum_{v=1}^{v} p_v x_v, \tag{4}$$

The derivation of the above equation utilizes the linear nature of IFFT. The grouped sub-block frequency domain signals are first subjected to an IFFT operation to obtain the time domain signal x_v. Subsequently, the transmitted signal x is constructed. Through this transformation, each iteration no longer performs the IFFT operation when searching for the optimal phase factor combination. This can greatly reduce computational complexity. The essence of the PTS algorithm is to enumerate all combinations of phase factors and calculate the PAPR for each combination of phase factors. By selecting different phase factors, different time domain signals x can be obtained, and the signal with the minimum PAPR for transmission can be selected. In this case, the PAPR of the output signal was lower than the original PAPR.

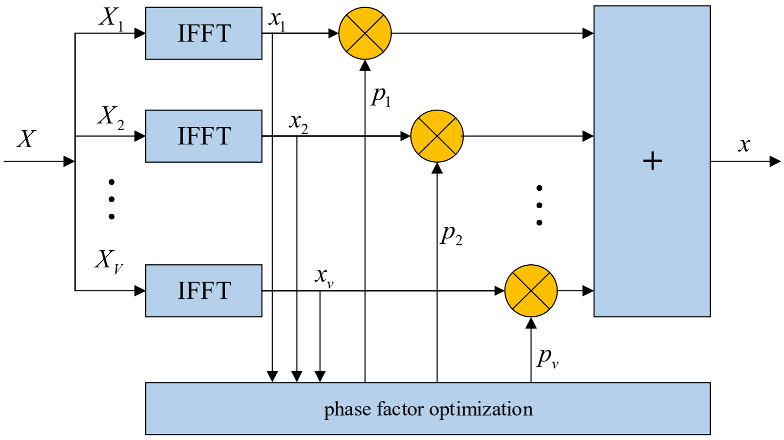

Figure 2. PTS algorithm schematic.

In the PTS algorithm, there are three main block partitioning methods for the original signal: adjacent, interleaved, and random. All three methods must satisfy the following conditions: subcarriers can only appear once and each block has the same number of subcarriers.

3. PTS Algorithm Based on DPSO and Improved Algorithm

3.1. Principle of DPSO

The idea behind the PSO algorithm originates from the group behavior of animals, such as bird flocks. The essence of the algorithm is that individuals in the group evolve by comparing their historical information while simultaneously comparing the information of the optimal individuals in the group. Individuals continuously coordinate and share information among themselves such that the movement of the entire group evolves iteratively in the problem-solving space and finally finds the optimal solution [24]. The most significant advantages of the PSO algorithm are its simplicity and rapid convergence.

Problems solved by the PSO algorithm are categorized as continuous and discrete problems. The problem to be solved in this study is discrete; therefore, the PSO proposed in this study is discrete, denoted as DPSO. The DPSO algorithm treats the individuals in a population as particles with only two physical quantities: position and velocity. The position of each particle represents a candidate solution in the solution space of the problem. A flowchart of the DPSO algorithm is presented in Figure 3.

The initial particle population is generated by randomization. In the iterative optimization process, it is assumed that the i^{th} particle position is $W_i = (b_{i1}, b_{i2}, \ldots, b_{iV})$, and the particle velocity is $V_i = (v_{i1}, v_{i2}, \ldots, v_{iV})$. Each particle's historical optimal position is denoted as $W_i^p = \left(b_{i1}^p, b_{i2}^p, \ldots, b_{iv}^p\right)$, and the historical optimal position in the population is denoted as $W^G = (b_1^G, b_2^G, \ldots, b_v^G)$. The particle's historical optimal position W_i^p and the historical optimal position in the population W^G affect the direction and speed of each particle's movement. By comparing the fitness values, each particle continuously corrects its movement direction and moves towards the optimal position after many iterations. Finally, the particles in the entire population move to the neighborhood of the optimal solution.

The velocity and position update equations for the DPSO are as follows [25]:

$$\begin{array}{c} v_{id}(t+1) = \omega * v_{id}(t) + c_1 * rand * (w_{id}pbest(t) - w_{id}(t)) + \\ c_2 * rand * (w_d gbest(t) - w_{id}(t)) \end{array}, \tag{5}$$

$$S(v_{id}(t+1)) = \frac{1}{1 + \exp(-v_{id}(t+1))}, \tag{6}$$

$$w_{id}(t+1) = \begin{cases} 1, & rand < S(v_{id}(t+1)) \\ 0, & \text{othercase} \end{cases}, \tag{7}$$

where Equation (5) is the velocity update formula, and $v_{id}(t+1)$ denotes the velocity of the i^{th} particle in the d^{th} dimension in the $(t+1)^{th}$ iteration. Equation (6) is the sigmoid mapping, which maps the particle's velocity to the interval [0, 1], and represents the probability that the particle's position will take 1 in the next iteration. Equation (7) is the position update formula and $w_{id}(t+1)$ denotes the position of the i^{th} particle in the d^{th} dimension at the $(t+1)^{th}$ iteration. The velocity update equation comprises three parts:

(1) $\omega * v_{id}(t)$ is the inertial component that represents the retention of a particle's speed of motion from the previous generation and ω is the inertial factor;
(2) $c_1 * rand * (w_{id}pbest(t) - w_{id}(t))$ is the self-awareness component that denotes the self-learning component of a particle and c_1 is the self-learning factor. For the best individual particle, $w_{id}pbest(t)$ denotes the optimal position of the i^{th} particle in the d^{th} dimension in the t^{th} iteration;
(3) $c_2 * rand * (w_d gbest(t) - w_{id}(t))$ is the social cognitive component that represents the learning component of a particle for the population, and c_2 is the social learning factor. As the global best, $w_d gbest(t)$ denotes the optimal population position in the d^{th} dimension at the t^{th} iteration and *rand* denotes a random number in [0, 1].

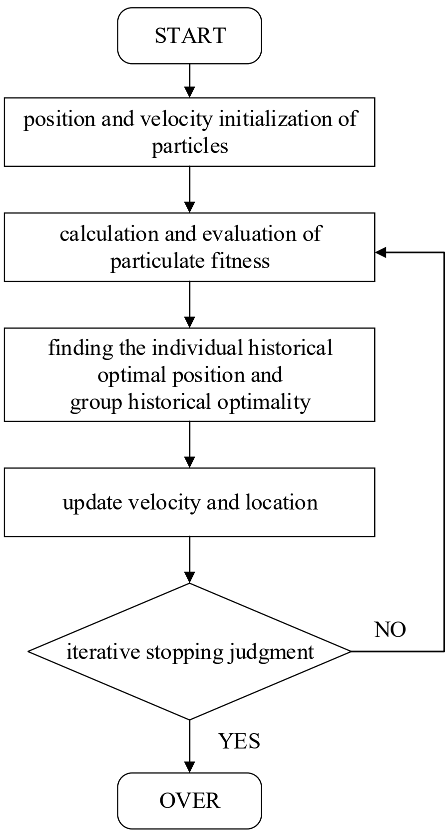

Figure 3. Flowchart of DPSO algorithm.

3.2. Fundamentals of DPSO-PTS Algorithm

According to the principle of the PTS algorithm, the dimensions of the position and velocity vectors of the particulate units are the number of partitions V in the PTS algorithm. The phase factors in the PTS method are considered finite, and in general, the number of phase factors is $M = (2, 4, 8)$. Each position of a particle represents a phase factor combination; for example, if the set of phase factors is $\{-1, 1\}(M = 2)$, then b_{iv} is considered to be either 0 or 1. Let 0 represent -1 for the V^{th} dimension of the i^{th} particle (i.e., the phase factor chosen for multiplication in the V^{th} sub-block), and let 1 represent 1 for the V^{th} dimension of the i^{th} particle. For $M = 4$, the set of phase factors is $\{-1, j, 1, -j\}$. Each dimension of b_{iv} in the particle's position is represented by a two-bit binary number, that is, (0,0), (0,1), (1,0), and (1,1) represents the choice of a different phase factor, and the number of binary digits representing the position of the particle is $\log_2 M$.

From the principles of DPSO and PTS, the PTS algorithm based on DPSO, denoted as DPSO-PTS, can be obtained as follows. The pseudo-code of the DPSO-PTS algorithm is shown in Algorithm 1.

Algorithm 1. The pseudo-code of DPSO-PTS algorithm.

Input: number of subcarriers N, particle swarm population size NUM,
inertia factor ω, maximum speed $V_{\max}$, learning factor c_1, c_2
maximum number of iterations Gn
Output: the global best W^G and corresponding PAPR value
Initialize: initialize the particle position W_i, particle velocity V_i,
fitness = $f(W_i)$, the initial individual particle best $W_i^p = W_i$,
the global best $W^G = \max(W_i^p)$.
for t = 1:Gn **do**
according to Equations (5)–(7), update the $v_{id}(t+1)$ and $w_{id}(t+1)$ of each particle in each dimension.
calculate the new fitness = $f(w_{id}(t+1))$.
if new fitness > fitness **then**
update W_i^p, $W^G = \max(W_i^p)$, fitness = new fitness.
else
remain the W_i^p, W^G, fitness.
end
end
get the PAPR value = $f(W^G)$

Step 1: System parameters and population initialization: Set the particle population size NUM; initialize the inertia factor ω, learning factors c_1 and c_2, and the maximum velocity limit $V_{\max}$; randomly generate NUM particles with position and velocity as the original population.

Step 2: Fitness calculation: First, calculate the PAPR value of the phase factor represented by the position of each particle, and calculate the reciprocal of the PAPR value as the fitness value. Initialize it to the optimal position of the particle and the corresponding optimal fitness value. Subsequently, select the optimal particle in the group, that is, the particle with the largest fitness value, as the initial optimal position and fitness value of the group.

Step 3: Update the velocity and position: Iteratively update the velocity and position of each particle. When the velocity exceeds the boundary range, it is equal to the maximum value set by the system parameters.

Step 4: Update the optimal position and its fitness: Recalculate the fitness value according to the latest positions of the particles; compare the individual particles with their historical information. If the new fitness value is greater, update the optimal position and fitness value. Otherwise, keep them unchanged. Simultaneously, we determine the optimal position in the group as the updated optimal position and fitness value of the group.

Step 5: Algorithm end judgment: The end condition of the algorithm can be set as the number of iterations or performance requirements. If the iteration satisfies the end condition, stop, and output; otherwise, return to Step 3.

3.3. Improved Algorithm MDPSO-PTS

Further analysis of the velocity updating formula proposed in the previous subsection comprises three parts, with the second and third terms representing the self-learning term and the social learning term, respectively. According to the different values of parameters c_1 and c_2, the DPSO-PTS optimization model can be divided into three cases:

(1) $c_1 \neq 0, c_2 = 0$, the velocity update formula contains only the inertia part and the self-awareness part, and can be referred to as the "self-awareness model". In this case, only the particle's information is considered, and it is only compared with its historical optimal position, but is not influenced by social information; that is, it lacks learning from the optimal particles in the population. This model is not prone to precociousness, but has a slow convergence rate;
(2) $c_1 = 0, c_2 \neq 0$, the velocity update formula contains only the inertial part and the socio-cognitive part, which can be referred to as the "socio-cognitive model". There is no self-learning process, no comparison with its historical optimal position, and only group learning exists. The model converges faster but is prone to precociousness and treats the local optimum as the global optimum;
(3) $c_1 \neq 0, c_2 \neq 0$, the velocity updating formula contains the inertia part, self-cognition part, and social cognition part, which can be referred to as the "full model". This model combines the advantages of the "self-cognitive model" and the "social cognitive model". This model employs a regional search centered on $w_{id}pbest(t)$ and $w_d gbest(t)$, which includes an individual's best historical position and the best historical position within the group. This balances the influences of both group and individual factors.

The "full model", c_1 is used to control the tendency of the particles to learn from their historical optimal positions, and c_2 is used to control the tendency of the particles to learn from the historical optimal positions in the population. The magnitudes of c_1 and c_2 represent whether the particles tend to move to their historical optimal positions or the global historical optimal positions. It is suggested that c_1 and c_2 satisfy $c_1 + c_2 \leq 4$. Existing studies consider $c_1 = c_2 = 2$ [26].

In this study, dynamic time-varying linearly decreasing and linearly increasing learning factors are proposed, and the improved algorithm focuses on the assignment of c_1 and c_2. The learning factors are represented as follows:

$$c_1(t) = 2.5 - \frac{2t}{Gn}, \tag{8}$$

$$c_2(t) = 0.5 + \frac{2t}{Gn}, \tag{9}$$

In the learning factor expression, Gn represents the maximum number of iterations, $t = 1, 2, 3 \cdots Gn$. $c_1(t)$ decreases linearly from 2.5 to 0.5, and $c_2(t)$ increases linearly from 0.5 to 2.5. In the early iterations of the proposed model, the particle focuses on learning its optimal position. The strength of the reference self-information is greater than that of social information, and the step size of a particle moving toward its historical optimal position decreases linearly with the number of iterations. In subsequent iterations, the particle focuses on learning the global optimal position. The strength of the reference social information is greater than that of its own, and the step size of the particle moving toward the global historical optimal position increases linearly with the number of iterations. In the early stages of the algorithm, the step length of the particle moving towards its historical optimal position is longer than that of the particle moving towards the global historical optimal position. This can prevent the particles from entering a precocious state. If an individual in a population is close to a better solution, then it becomes the current best solution. When individuals in the population move towards the population's best solution with high speed and a strong tendency, the entire population quickly converges to that individual, mistakenly considering the current local optimum as the global optimum. The limited exploration of feasible solutions by the population and the small search space can result in a potential false optimal solution, leading to a degradation in the PAPR suppression performance. Therefore, in early iterations, it is crucial to expand the search space of the particles as much as possible. Each individual in the population should explore the surrounding areas for better solutions, move towards them, and search for more feasible solutions. This approach is necessary to find globally superior solutions. In the later stages of the algorithm, the particles move with a larger step size towards the global best historical position than to their best historical position. This larger step size results in a stronger trend as the particles converge towards the global optimal solution. Consequently, the entire population converges near the optimal solution, thereby ensuring the convergence speed of the algorithm.

4. Simulation and Analysis

4.1. Simulation Experiments Settings

According to the PTS principle, the number of subcarrier partition blocks and phase factors are the main parameters affecting the PAPR reduction performance. MATLAB simulation experiments were conducted to analyze the effects of these two parameters on PAPR reduction performance.

The improved MDPSO-PTS algorithm employs the dynamic and time-varying learning factors proposed in Section 3.3. The DPSO-PTS algorithm adopts the conventional learning factor $c_1 = c_2 = 2$. Comparative simulation experiments were conducted using the two algorithms.

Simulation Experiment 1 was conducted to analyze the PAPR reduction performance of the MDPSO-PTS and DPSO-PTS algorithms for different numbers of partitions. Set the numbers of partitions $V = 8, V = 16$. The parameters for Simulation Experiment 1 are listed in Table 1.

Table 1. Simulation experiment parameters.

Parameters	Value
Number of subcarriers N	256
Mapping	QPSK
Partition method	adjacent partition
Phase factor	$P_V = \{1, -1\}(M = 2)$
Number of partitions	$V = 8, V = 16$
Particle swarm population size NUM	5
Inertia factor ω	0.85
Maximum speed limit $V_{\max}$	2
Maximum number of iterations Gn	10
Number of OFDM symbols	1000

Simulation Experiment 2 was conducted to analyze the PAPR reduction performance of the MDPSO-PTS and DPSO-PTS algorithms for different phase factor numbers. Set phase factor $P_V = \{1, -1\}(M = 2)$, $P_V = \{1, j, -1, -j\}(M = 4)$. Set the fixed number of partitions as $V = 8$. The other parameters for Simulation Experiment 2 are listed in Table 1.

Simulation Experiment 3 was conducted to analyze the PAPR reduction performance of the MDPSO-PTS algorithm for different numbers of iterations Gn. We also compared the PAPR reduction performances of the improved and conventional PTS algorithms. Set the number of iterations $Gn = [2, 4, 8, 10, 15, 20]$ for the MDPSO-PTS algorithm, the fixed number of partitions $V = 8$ and fixed phase factor $P_V = \{1, -1\}(M = 2)$. The other parameters for Simulation Experiment 3 are listed in Table 1.

Simulation Experiment 4 focuses on the average PAPR curve variation for different numbers of iterations using the MDPSO-PTS algorithm. Set the number of iterations $Gn = [0 : 2 : 20]$ and maintain the number of partitions $V = 8$ and phase factor $P_V = \{1, -1\}(M = 2)$. The iteration $Gn = 0$ represents the average PAPR value of the original OFDM signal without the MDPSO-PTS algorithm. The other parameters for Simulation Experiment 4 are listed in Table 1.

4.2. Analysis of Simulation Experiment Results

Figure 4 shows the results of Simulation Experiment 1, comparing the DPSO-PTS and MDPSO-PTS algorithms with different numbers of partitions, V.

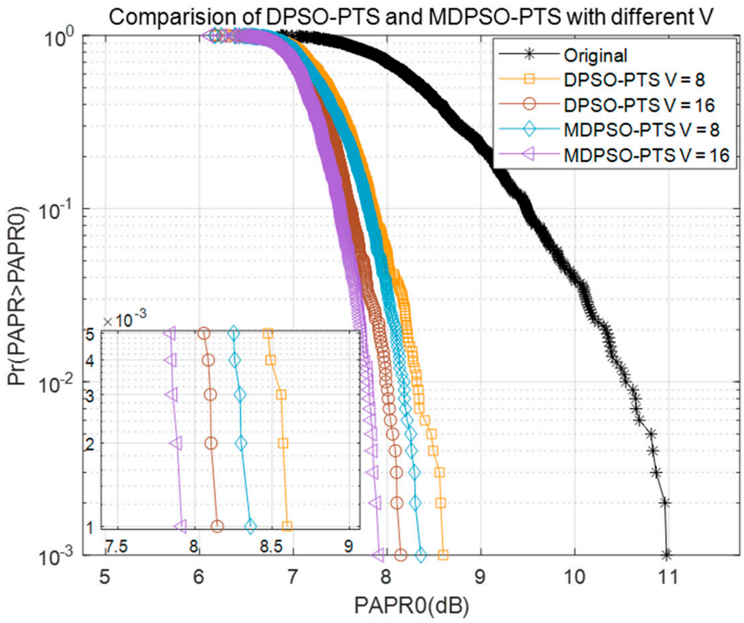

Figure 4. Comparison of DPSO-PTS and MDPSO-PTS algorithms with different divided blocks V.

Both the MDPSO-PTS and DPSO-PTS algorithms effectively reduced the PAPR of the OFDM system. With an increase in the number of subcarrier partition blocks, the performance in reducing the PAPR increased significantly. For different numbers of partition blocks $V = 8, V = 16$, the proposed MDPSO-PTS algorithm exhibited an overall superior performance in terms of PAPR reduction compared with the DPSO-PTS algorithm. During $Pr(\text{PAPR} > \text{PAPR0}) = 10^{-3}$, the PAPR value of the original OFDM signal without PAPR reduction using the MDPSO-PTS or DPSO-PTS algorithm was 10.98 dB. The PAPR value with the MDPSO-PTS algorithm decreased to 8.36 dB, and 7.91 dB, respectively, and the PAPR with the DPSO-PTS algorithm decreased to 8.60, and 8.14 dB, respectively. For partition blocks $V = 8$, the performance of the proposed improved MDPSO-PTS algorithm increased by 0.24 dB over the unimproved DPSO-PTS algorithm. For the partition blocks $V = 16$, the performance of the improved algorithm increased by 0.23 dB.

Figure 5 shows a comparison of the DPSO-PTS and MDPSO-PTS algorithms with different numbers of phase factors M in Simulation Experiment 2. It can be observed that the PAPR reduction performance increased with an increase in the number of phase factors. During $Pr(\text{PAPR} > \text{PAPR0}) = 10^{-3}$, the PAPR value of the original OFDM signal without PAPR reduction using the MDPSO-PTS or DPSO-PTS algorithm was 11.00 dB. For $P_V = \{1, -1\}(M = 2)$ and $P_V = \{1, j, -1, -j\}(M = 4)$, the proposed MDPSO-PTS algorithm outperformed the DPSO-PTS algorithm for PAPR reduction in both cases. The PAPR values using the MDPSO-PTS algorithm were reduced to 8.38 dB and 8.09 dB, respectively, and the PAPR values using the DPSO-PTS algorithm were reduced to 8.57 dB, and 8.29 dB, respectively. For $P_V = \{1, -1\}(M = 2)$, the performance of the proposed improved MDPSO-PTS algorithm increased by 0.19 dB compared with the DPSO-PTS algorithm. For $P_V = \{1, j, -1, -j\}(M = 4)$, the performance of the improved algorithm increased by 0.20 dB.

Simulations 1 and 2 demonstrate the superiority of the improved algorithm. The MDPSO-PTS algorithm adopts a time-varying dynamic learning factor and focuses on moving to the particle's historical optimal position in the early iteration. This can prevent the particle from entering precocious maturity too early, treating the local optimal solution as a global optimal solution, and prevent convergence in advance. In the later iteration, it focuses on moving to the global optimal position, which ensures convergence speed. The complexity of the MDPSO-PTS algorithm was similar to that of the DPSO-PTS algorithm, remaining almost unchanged.

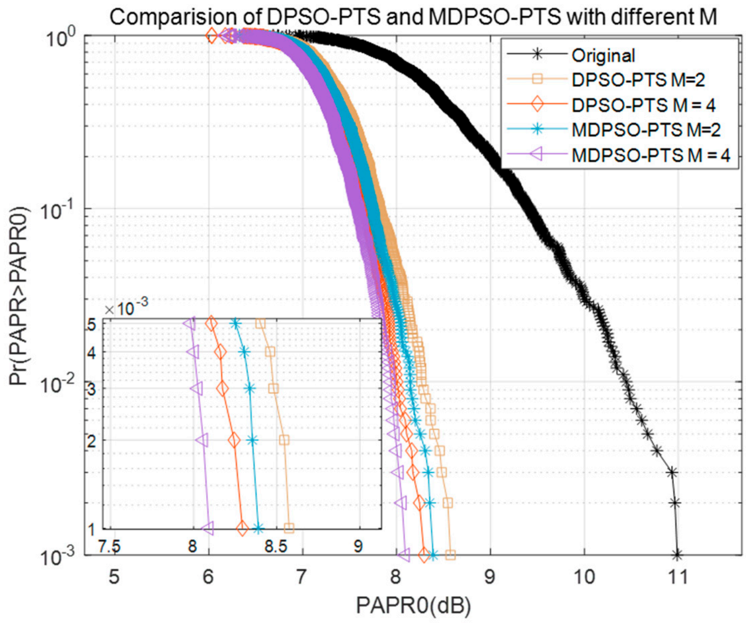

Figure 5. Comparison of DPSO-PTS and MDPSO-PTS algorithms with different phase factors M.

The results of Simulation Experiment 3, comparing the MDPSO-PTS algorithm with different numbers of iterations of Gn and the traditional PTS algorithm, are shown in Figure 6. The curve-labeled PTS in the figure is the traditional PTS algorithm, which enumerates all the sets of phase factors by sacrificing a large amount of computational complexity. Different phase factors resulted in different PAPR values. The selection of an optimal combination of phase factors can yield the best PAPR reduction performance. According to Figure 6, the PAPR reduction performance of the MDPSO-PTS algorithm gradually increased as the number of iterations increased. During $Pr(\text{PAPR} > \text{PAPR0}) = 10^{-3}$, the PAPR value of the original OFDM signal without PAPR reduction by the MDPSO-PTS or PTS algorithm was 10.80 dB. When the MDPSO-PTS algorithm was used, for different numbers of iterations $Gn = [2, 4, 8, 10, 15, 20]$, the PAPR value decreased to 8.71 dB, 8.54 dB, 8.30 dB, 8.20 dB, 8.02 dB, and 7.97 dB. The reduction in the PAPR value of the original OFDM signal was enhanced by 2.09 dB, 2.26 dB, 2.50 dB, 2.60 dB, 2.78 dB, and 2.83 dB. The PAPR value using the traditional PTS algorithm decreased to 7.87 dB, which enhanced the reduction performance by 2.93 dB with respect to the PAPR value of the original OFDM signal. When the numbers of iterations $Gn = 15$ and $Gn = 20$ were increased by 5 and 10 iterations, respectively, over the number of iterations $Gn = 10$, the increment in the PAPR reduction effect was 0.18 dB and 0.05 dB. The increment in the reduction effect decreased significantly when the number of iterations increased to $Gn = 10$.

The variation of the average value of PAPR for different numbers of iterations in Simulation Experiment 4 is analyzed in Figure 7, and the curve is a gradually flattening one. When the number of iterations was greater than 10, the decrease was smaller and the increment of performance improvement was smaller. Therefore, for different scale scenarios of PAPR reduction, experiments were needed to derive the optimal number of iterations to avoid adding too much iteration complexity with only a minimal increase in performance.

The performance of the MDPSO-PTS algorithm is compared with that of the conventional PTS algorithm in Figure 6. When the number of iterations was $Gn = 10$, $Gn = 15$, and $Gn = 20$, the performance of the MDPSO-PTS algorithm was only reduced by 0.33 dB, 0.15 dB, and 0.10 dB, respectively. The MDPSO-PTS algorithm sacrificed a small amount of PAPR for PAPR reduction performance, but reduced computational complexity. For the number of partition blocks $V = 8$ and phase factors $P_V = \{1, -1\}(M = 2)$ in this simulation experiment, the traditional PTS algorithm needed to calculate 128 times the PAPR value. The number of times the PAPR value needed to be calculated was M^{V-1}. In contrast, the MDPSO-PTS algorithm with an iteration number of $Gn = 10$, $Gn = 15$, and $Gn = 20$ needed to calculate 50 times, 75 times, and 100 times, respectively. The number of PAPR value calculations was the product of the population size and the number of iterations. The PAPR reduction performance of the improved algorithm with an iteration number of $Gn = 15$ was reduced by 0.15 dB compared with the traditional PTS algorithm, and its complexity was reduced to only 58.6% of the traditional PTS algorithm. By choosing the appropriate number of iterations, computational complexity can be reduced while only losing a smaller PAPR reduction performance. For more partition blocks and phase factors, the computational complexity of the traditional PTS increased exponentially. However, the computational complexity of the MDPSO-PTS algorithm was related to the population size and the number of iterations, and the computational complexity was unchanged. Therefore, the proposed MDPSO-PTS algorithm had excellent PAPR reduction performance, and its effect was more obvious for the scenarios with a large number of partitions and phase factors.

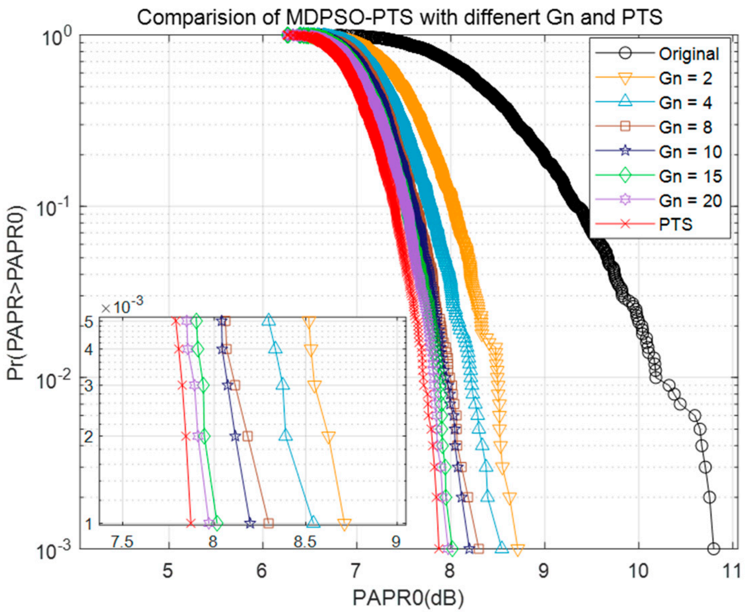

Figure 6. Comparison of MDPSO-PTS algorithm with different iterations *Gn* and PTS algorithm.

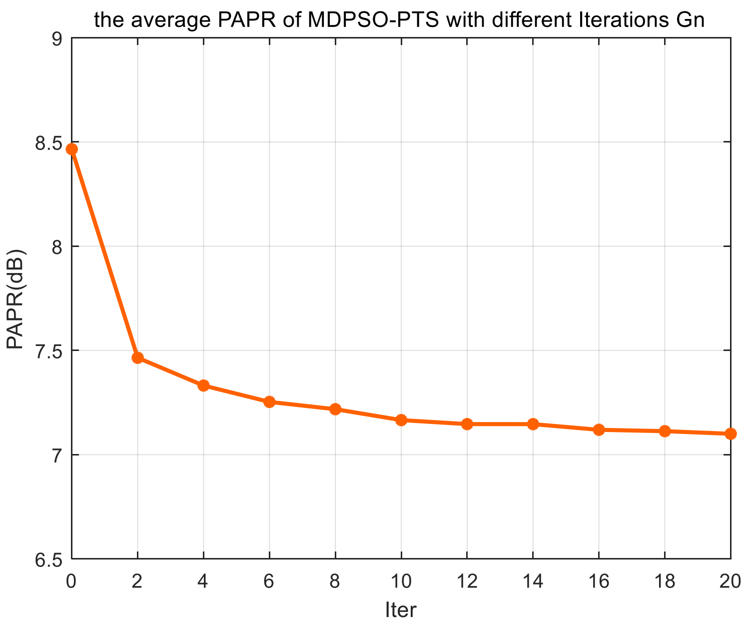

Figure 7. Average PAPR of MDPSO-PTS algorithm with different iterations *Gn*.

5. Conclusions

In this paper, an improved MDPSO-PTS algorithm that introduces dynamic time-varying learning factors is proposed. This enhances the accuracy and efficiency of the DPSO-PTS algorithm in searching for phase factors. By incorporating the dynamic and time-varying nature of learning factors, the MDPSO-PTS algorithm avoids the premature convergence drawback of the DPSO-PTS algorithm. This expands the search space and prevents early convergence and becoming trapped in local optima. The simulation results show that the proposed improved MDPSO-PTS algorithm has a better PAPR reduction capability than the unimproved DPSO-PTS algorithm. Compared with the traditional globally optimal search PTS algorithm, the improved MDPSO-PTS algorithm exhibited slightly reduced performance but significantly lower computational complexity. The complexity reduction was more evident when the number of partition blocks and phase factors increased.

PAPR reduction is especially important for OFDM communication systems, and superior PAPR reduction algorithms can significantly improve the communication system performance. Low-complexity PAPR reduction algorithms can reduce signal processing latency, enhance communication speed, reduce hardware requirements, and reduce costs. The proposed improved algorithm demonstrated excellent capabilities in reducing the complexity and enhancing the reduction performance, thereby significantly improving the performance of communication systems.

The main advantage of the proposed MDPSO-PTS algorithm is its distortion-free nature, which prevents signal loss. Its drawback lies in its weaker PAPR reduction capability compared with methods such as clipping or companding, which are simple but result in signal distortion and an increase in the BER of the system. Future research can explore the combination of clipping or companding with the MDPSO-PTS method to develop a joint algorithm that meets the system requirements in terms of BER, complexity, and PAPR reduction capability. Moreover, the proposed algorithm is applicable to MIMO-OFDM systems, allowing the integration of this PAPR algorithm with MIMO-OFDM systems to satisfy the requirements of high-rate communications.

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