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Partial Transmit Sequence Optimization Using Improved Harmony Search Algorithm for PAPR Reduction in OFDM

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This paper considers the use of the Partial Transmit Sequence (PTS) technique to reduce the Peak-to-Average Power Ratio (PAPR) of an Orthogonal Frequency Division Multiplexing signal in wireless communication systems. Search complexity is very high in the traditional PTS scheme because it involves an extensive random search over all combinations of allowed phase vectors, and it increases exponentially with the number of phase vectors. In this paper, a suboptimal metaheuristic algorithm for phase optimization based on an improved harmony search (IHS) is applied to explore the optimal combination of phase vectors that provides improved performance compared with existing evolutionary algorithms such as the harmony search algorithm and firefly algorithm. IHS enhances the accuracy and convergence rate of the conventional algorithms with very few parameters to adjust. Simulation results show that an improved harmony search-based PTS algorithm can achieve a significant reduction in PAPR using a simple network structure compared with conventional algorithms.

Keywords: Improved harmony search (IHS), Orthogonal frequency division multiplexing (OFDM), Peak-to-average power ratio (PAPR), Traditional partial transmit sequence (T-PTS).

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I. Introduction

Orthogonal frequency division multiplexing (OFDM) systems are employed in a variety of wireless broadband communication systems such as Digital Audio Broadcasting (DAB), Terrestrial Digital Video Broadcasting (DVB-T), wireless LAN, WiMAX, and the smart grid system. In spite of their desirable qualities, OFDM systems have a major drawback with regard to large envelope variations resulting in high a Peak-to-Average Power Ratio (PAPR). This significantly reduces the power efficiency of the system. Hence, efficient methods for PAPR reduction are essential in high-speed wireless communication systems.

In addition, reduction in PAPR is instrumental in the removal of nonlinear effects and improvement in the power efficiency of power amplifiers. Several PAPR reduction schemes have been proposed in the literature, including signal predistortion techniques, coding techniques, and multiple signaling and probabilistic techniques [1]. Signal distortion techniques include clipping and filtering [2], peak windowing [3], companding [4], and peak cancellation [5]. These techniques reduce the PAPR significantly, but they also introduce in-band and out-of-band distortion.

Coding techniques have the capability to provide error detection and correction [6]. These techniques perform PAPR reduction by modifying these coding schemes to provide both functions with an acceptable extra complexity. Multiple signaling and probabilistic techniques generate either multiple permutations of the OFDM signal and transmit the one with minimum PAPR, or modify the OFDM signal by introducing phase shifts, adding peak reduction carriers, or changing constellation points [7].

In probabilistic techniques, the Partial Transmit Sequence (PTS) has been the most promising one owing to its excellent PAPR reduction capability without restrictions on the number of subcarriers [8]. In PTS, the data block is divided into disjoint sets called subblocks. The subblocks are combined, followed by multiplication of a phase vector. In PTS, the design of the optimal transmit phase selection of the optimum phase vector from a set of known solutions is the most challenging issue because the computational complexity is very high for a large number of subcarriers [9].

In this paper, the conventional PTS scheme is mentioned as Traditional PTS (T-PTS). In T-PTS, the exhaustive search space for an optimal phase factor increases exponentially with the number of subblocks [10]. The increase in the search space leads to an increased computational complexity.

Nature-inspired approaches have attracted the attention of researchers for solving a variety of optimization problems [11]. The Particle Swarm Optimization based PTS (PSO-PTS) is proposed in [12] for Quadrature Phase Shift Keying (QPSK) modulated OFDM signals. It has optimum search complexity, but the PAPR reduction is not as effective as others in evolutionary techniques. Wang and others proposed a PAPR reduction method based on an Artificial Bee Colony PTS (ABC-PTS) algorithm for OFDM systems [13], which provides a wider search space. However, ABC-based algorithms suffer from low convergence speeds.

For an iteration-based approach, Taspinar and others tried to solve the PAPR reduction problem with a Tabu-Search-based PTS scheme [14]. This method not only reduced the PAPR significantly but also reduced the computational search complexity. Firefly-algorithm-based PTS (FF-PTS) was proposed in [15] for Quadrature Amplitude Modulated (QAM) modulated OFDM signals. It had less computational complexity owing to its simple structure, and very few parameters to adjust for larger PTS subblocks. However, the PAPR reduction was not as good as those of evolutionary algorithms.

Recently, the Shuffled Frog Leaping algorithm [16] was proposed by Zhou and others. This algorithm provides a better performance-complexity trade-off than the existing approaches. Compared with the existing PAPR reduction methods, the HS-PTS [17] algorithm can obtain better PAPR reduction owing to its simple structure and few parameters to adjust. Other useful heuristic algorithms include the Genetic algorithm [18] and Bacterial Foraging algorithm [19], which provide lower PAPRs than conventional PTS algorithms.

The harmony search algorithm received the attention of many researchers in solving a variety of optimization problems in engineering and computer science [20]. The Harmony-Search-based PTS algorithm (HS-PTS) was presented by Kermani and others in [17], [21]. The proper selection of HS parameter values is considered a challenging task for HS algorithms, as it is in other metaheuristic algorithms. The initializing parameter is problem dependent, and therefore experimental trials are the only guide to the best values. However, this matter guides the research into new variants of HS.

An improved harmony search algorithm based on harmony search was recently proposed [22]. This design was conceptually similar to the HS algorithm and was effective for solving combinatorial optimization problems. Two parameters, the Pitch Adjustment Rate (*PAR*) and distance bandwidth (*bw*), are initialized and fixed in the HS algorithm. It exhibits low performance and a greater number of iterations are needed to find the optimal solution. Adjusting *PAR* and *bw* in each improvisation step gives better optimal solutions. On the other hand, these parameters have low values for the exploitation of an optimal solution in the final stages. This provides a suboptimal solution to enhancing the performance of the conventional HS algorithm. This paper provides a performance analysis of PAPR reduction in OFDM using this improved harmony search algorithm, as compared with FF-PTS [15] and HS-PTS [17].

The rest of this paper is organized as follows. In Section II, a PTS-based OFDM signal is analyzed with regard to PAPR and a Complementary Cumulative Distribution Function (CCDF). In Section III, evolutionary optimization algorithms such as Firefly (FF), harmony search (HS), and its variant improved harmony search (IHS) are explained, and the proposed IHS-PTS algorithm is described. The performance of the proposed IHS-PTS is compared with the conventional T-PTS, and state-of-the-art HS-PTS and FF-PTS techniques are evaluated based on variations in the number of subblocks, subcarriers, and iterations in Section IV. Finally, the paper is concluded in Section V.

II. Partial-Transmit-Sequence-Based OFDM System

1. Peak-to-Average-Power Ratio of OFDM

OFDM is a multicarrier modulation technique in which a block of N data symbols $\{X_n, n = 0, 1, \ldots, N-1\}$ form one OFDM signal to be transmitted using one subcarrier for each symbol. The transmit bit stream is divided into several orthogonal subcarriers, each modulated at a low rate [23]. Each OFDM signal modulates a different subcarrier from the set $\{f_n, n = 0, 1,$

. . . , $N-1\}$. The N subcarriers are orthogonal, that is, $f_n = n\Delta f$, where $\Delta f = 1/NT$, and T is the symbol period. The complex baseband representation of a multicarrier signal consisting of N subcarriers is given by

$$x(t) = \frac{1}{\sqrt{N}}\sum_{n=0}^{N-1} X_n e^{j2\pi f_n t}, \quad \text{where} \quad 0 \le t \le NT. \tag{1}$$

Per the definition, the PAPR of the transmitted signal is the ratio of the peak power to the average power of the signal, that is,

$$\text{PAPR} = \frac{\max\limits_{0\le t\le NT}|x(t)|^2}{E\left[|x(t)|^2\right]}. \tag{2}$$

Usually, CCDF is used to show performance measures for PAPR reduction techniques. It calculates the probability that the PAPR of a data block exceeds a given threshold PAPR_0, and is computed by a Monte Carlo simulation [24]. The CCDF of a PAPR of N symbols of a data block with a Nyquist rate sampling is defined as

$$\begin{aligned} P_r(\text{PAPR} > \text{PAPR}_0) &= 1 - P_r(\text{PAPR} \le \text{PAPR}_0) \\ &= 1 - \left(1 - e^{-\text{PAPR}_0}\right)^N. \end{aligned} \tag{3}$$

The CCDFs are generally used to represent the PAPR of an OFDM signal.

2. Traditional Partial Transmit Sequence Technique

In the Traditional Partial Transmit Sequence (T-PTS) technique, an entire data block X of length N is partitioned into M disjoint subblocks. The IFFT for each of these subblocks is computed separately, and is then multiplied by a phase vector. This is the stage where phase optimization techniques are employed to determine the optimal phase vector to provide the lowest PAPR. Figure 1 shows a block diagram of the OFDM transmitter with the PTS technique.

Let the input data block $X = [X_1, X_2, \ldots, X_N]$ be partitioned into M disjoint subblocks $X_m = [X_{m1}, X_{m2}, \ldots, X_{m,N}]$, where $m = 1, 2, \ldots, M$. These subblocks are orthogonal to each other, and X is the combination of all M subblocks:

$$X = \sum_{m=1}^{M} X_m. \tag{4}$$

Then, the IFFT of individual subblock x_m is computed, where $m = 1, 2, \ldots, M$, and will be multiplied by a phase vector $b_m = e^{j\phi_m}$, where $\phi_m = (0, 2\pi)$ and $m = 1, 2, \ldots, M$. After this, only the sets with optimal phase vectors b_m having the lowest PAPR of the combined time domain signal x is to be transmitted, where x is defined as

$$x(b) = \sum_{i=1}^{M} b_i x_i, \tag{5}$$

where $x(b) = [x_1(b), x_2(b), \ldots, x_N(b)]$.

The T-PTS technique involves the selection of an OFDM signal with a lesser phase factor set and due to that, complexity will be increased. This method requires the transmitter to track the information of the sent data blocks [25].

The main issue with the T-PTS technique is its complexity. The T-PTS technique requires all combinations of allowed phase factors for an optimum exhaustive search [10], which leads to an exponential rise in the number of subblocks. Subblock partitioning is another factor that affects the PAPR, which is a method of dividing subbands into multiple disjoint subblocks. There are three kinds of subblock partitioning scheme: adjacent, interleaved, and pseudorandom partitioning [26]. Of these, pseudorandom partitioning has been found to be the best choice. Thus, the T-PTS technique works with an arbitrary number of subcarriers and all modulation schemes [27].

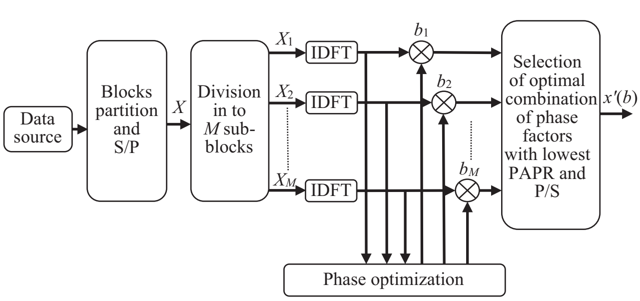

Fig. 1. Block diagram of traditional partial transmit sequence technique.

III. Improved Harmony Search PTS Optimization

In order to get the OFDM signals with the minimum PAPR, a suboptimal combinatorial method based on an improved harmony search (IHS) is proposed to solve the optimization problem of T-PTS.

The minimum PAPR for the PTS method is relative to the problem:

Minimize

$$f(b) = \frac{\max\left[|x(b)|^2\right]}{E\left[|x(b)|^2\right]}, \tag{6}$$

subject to

$$b \in \left\{e^{j\phi_m}\right\}^M, \tag{7}$$

where

$$\phi_m \in \left\{ \frac{2\pi k}{W} | k = 0, 1, \ldots, W - 1 \right\}.$$

The Improved Harmony Search PTS (IHS-PTS) algorithm can obtain a better PAPR performance as compared with the conventional firefly algorithm and the harmony search algorithm.

1. Firefly Algorithm

In the firefly algorithm, the objective function of a given optimization problem is based on differences in light intensity. It helps the fireflies to move toward brighter and more attractive locations to obtain optimal solutions. All fireflies are characterized by their light intensity, which is associated with the objective function. Each firefly changes its position iteratively [28].

Each firefly has attractiveness β, described by a monotonically decreasing function of the distance r between any two fireflies

$$\beta(r) = \beta_0 e^{-\gamma r^m}, m \geq 1, \tag{8}$$

where β_0 denotes the maximum attractiveness (at $r = 0$), and γ is the light absorption coefficient, which controls the decrease in light intensity. The distance between two fireflies i and j at positions b_i and b_j can be defined as follows:

$$r_{ij} = \|b_i - b_j\| = \sqrt{\sum_{k=1}^{d} \left(b_{i,k} - b_{j,k}\right)^2}, \tag{9}$$

where $b_{i,k}$ is the k-th component of the spatial coordinate b_i of the i-th firefly, and d denotes the number of dimensions. The movement of a firefly i is determined by the following equation:

$$b_i = b_i + \beta_0 e^{-\gamma r_{ij}^2}(b_j - b_i) + \alpha\left(rand - \frac{1}{2}\right), \tag{10}$$

where the first term is the current position of a firefly i, the second term denotes the firefly's attractiveness, and the last term is used for random movement if there are no brighter fireflies [*rand* is a random number generator uniformly distributed in the range (0, 1)]. In practice, the light absorption coefficient γ varies from 0.1 to 10. This parameter describes the variation of the attractiveness, and its value is responsible for the speed of the firefly algorithm's convergence. The search complexity of the FF-PTS algorithm is equal to $n^2(K)$.

2. Harmony Search Algorithm

Harmony Search is a music-based metaheuristic optimization algorithm that was inspired by the observation of a musician's improvisation process and aims to search for the perfect state of harmony in the music. A perfectly pleasing harmony is determined by the audio aesthetic standard. Similarly, the T-PTS technique searches for the best combination of phase vectors that gives the lowest PAPR and reduces the complexity as well [21]. The harmony search algorithm idealizes the improvisation process by a skilled musician. When a musician is improvising, a he or she has three possible choices [29]:

- Play any famous piece of music (a series of pitches in harmony) exactly from memory, which corresponds to harmony memory.
- Play something similar to a known piece (thus adjusting the pitch slightly), which corresponds to pitch adjustment.
- Compose new or random notes, which corresponds to randomization. A state of perfect harmony is reached by adjusting these three parameters. The steps involved in the conventional Harmony Search Algorithm are as follows:

Step 1: Initialization of all parameters, that is, upper bound, lower bound, harmony memory accepting or consideration rate (*HMCR*), Pitch Adjustment Rate (*PAR*), distance bandwidth (*bw*), harmony memory size (*HS*), and total number of improvisations (K).

Step 2: Populate the harmony memory with a possible set of solutions or harmonies randomly. This can be a matrix or vector such as

$$\text{HM} = \begin{bmatrix} b_1^1 & b_2^1 & \ldots & b_K^1 \\ b_1^2 & b_2^2 & \ldots & b_K^2 \\ \ldots & \ldots & \ldots & \ldots \\ b_1^{HMS} & b_2^{HMS} & \ldots & b_K^{HMS} \end{bmatrix}.$$

Step 3: Improvise the harmony by determining a new vector by adjusting the three parameters, that is, memory consideration, pitch adjustment, and random selection. Memory consideration determines whether the new vector will be generated by harmony memory values or in a random manner.

Step 4: If the new harmony is better than the previous worst-fit harmony, then it will be replaced by the new harmony. Otherwise, step 2 is repeated until the total number of function evaluations K is reached.

Algorithm 1. Harmony Search Algorithm

Define fitness function $f(b)$, $b = [b_1, b_2, \ldots, b_m]$, $m = 1, 2, \ldots, M$
Define *HMCR*, *PAR*, *HMS*
Define maximum number of iterations (K)
HM ← Generate initial phase factor vectors.
while iterative number $\leq K$ **do**
  while $m < M$ **do**
    if $rand \in (0, 1) \leq HMCR$ **then**
      choose a value from HM form
      if $rand \in (0, 1) \leq PAR$ **then**
        adjust the value of m by:
        $b_{m\_\text{new}} = b_{m\_\text{old}} * rand\{+1, -1\}$
      end if
  else
  choose a value from the possible solution collections $\{+1, -1\}$
  $b_{m\_\text{new}} = rand\{+1, -1\}$
  end if
  end while
  if $Fitness\ (b_{m\_\text{new}}) \leq$ Max(*Fitness*(*HM*)) **then**
accept the new phase factor, and replace the worst one in HM with it
end if
end while
best = find the current best phase factor

Various variants of harmony search algorithms are available in the literature [30].

3. Improved Harmony Search Algorithm

The performance of any metaheuristic algorithm such as the harmony search depends on two factors: exploration and exploitation. The optimal and balanced combination of these two contradicting factors determines the efficiency of the algorithm. The Improved Harmony Search Algorithm attempts to enhance the accuracy and convergence rate of the harmony search by adjusting the *PAR* and *bw* to be updated dynamically as

$$PAR(k) = PAR_{\min} + \left(\frac{PAR_{\max} - PAR_{\min}}{K}\right)k, \qquad (11)$$

$$bw(k) = bw_{\max} \exp\left(\frac{\ln(bw_{\min}/bw_{\max})}{K}\right)k, \qquad (12)$$

where k and K represent the current number of improvisations and the maximum number of improvisations, respectively. As PAR and *bw* are initialized and fixed in the conventional HS algorithm, it exhibits low performance and a higher number of iterations, which are needed for finding the optimal solution. Adjusting PAR and *bw* in each improvisation step gives a better convergence rate and leads to optimal solutions. These parameters are initially set high to find the diversity when searching for solution vectors in the harmony memory, so that all possible combinations are explored to a greater level. On the other hand, these parameters have low values for the exploitation of optimal solutions in the final stages. This results in a suboptimal solution to enhance the performance of the HS algorithm [22].

4. Improved Harmony Search-PTS Approach

The steps of the proposed IHS-PTS algorithm are as follows:

A. Parameter Initialization

The specified parameters are the harmony memory considering rate (*HMCR*) = 0.95, harmony memory size (*HMS*) (that is, the number of solutions available in memory = 16), pitch adjustment rate (*PAR*) = 0.05, number of musical instruments (that is, the number of each phase factor vector = *W*), pitch range of each instrument (that is, the value range of each phase vector = $\{+1, -1\}$), and stopping criterion K.

B. Harmony Memory Initialization

Harmony memory (HM) is initialized with a possible set of phase vectors. Each row in the matrix is a set of solutions obtained by evaluating the objective function between lower and upper bound values. This results in randomly populating the solutions for each structure ($i = 1, 2, \ldots, HMS$). The objective function $f(b)$ is evaluated, and will take its value from the collection of phase vector $\{+1, -1\}$.

C. New Solution Construction

In this step, the HS algorithm generates (improvises) a new harmony vector from scratch, $b \in \left\{e^{j\phi_m}\right\}^M$, based on three operators: (i) memory consideration, (ii) random consideration, and (iii) pitch adjustment.

a. Memory consideration

In memory consideration, the value of the first decision variable b'_1 is randomly selected from the historical values $b_i \in \left[b_{i,1}, b_{i,2}, \ldots, b_{i,HMS}\right]$, which are stored in the HM vectors. Values of the other decision variables,

$[b'_2, b'_3, \ldots, b'_M]$, are sequentially selected in the same manner with probability (w.p.) *HMCR*, where $HMCR \in (0,\ 1)$. It is worth noting that the selection scheme in memory consideration is random, and that the natural selection principle is not used.

b. Random consideration

Decision variables that are not assigned with values according to memory consideration are randomly assigned according to their possible range by random consideration with a probability of (1 – *HMCR*) as follows:

$$b'_i \leftarrow \begin{cases} b'_i \in \{b_{i,1}, b_{i,2}, \ldots, b_{i,HMS}\} \text{ with probability HMCR,} \\ b'_i \in \{e^{j\phi_m}\}^M \text{ with probability } (1-\text{HMCR}). \end{cases} \tag{13}$$

c. Pitch adjustment

Each decision variable b'_1 of a new harmony vector $[b'_1, b'_2, b'_3, \ldots, b'_M]$, which was assigned a value by memory consideration, is pitch adjusted with the probability of *PAR* where $PAR \in (0;1)$ as follows:

$$\text{Pitch adjustments for } b'_i \leftarrow \begin{cases} \text{Yes} \quad \text{with probability } PAR, \\ \text{No} \quad \text{with probability } (1-PAR). \end{cases} \tag{14}$$

If the pitch adjustment decision for b'_1 is Yes, the value of b'_1 is modified to its neighboring value as follows:

$$b'_i = b_i^{\min} + rand \in (0,1) \times (bw). \tag{15}$$

D. Update Harmony Memory

Updates to the harmony vector are accomplished by comparing the new harmony vector with the worst-fit solution. If the new vector is better than the worst solution, then it is replaced by the new harmony vector.

E. Stopping Criterion

The above algorithm is repeated until the total number of function evaluations *K* is reached. Otherwise, Step 2 is repeated. The search complexity in the IHS-PTS algorithm is equal to *MKW*.

The Improved Harmony Search Algorithm attempts to enhance the accuracy and convergence rate of the harmony search by adjusting the Pitch Adjusting Rate *PAR* and the distance bandwidth *bw* values. The *PAR* value linearly increases in each iteration of HS by the following relationship:

$$PAR(k) = PAR_{\min} + \left(\frac{PAR_{\max} - PAR_{\min}}{K}\right)k. \tag{16}$$

The bandwidth (*bw*) value is exponentially reduced in each iteration of HS by using the following equation:

$$bw(k) = bw_{\max} \exp + \left(\frac{\ln(bw_{\min}/bw_{\max})}{K}\right)k. \tag{17}$$

Algorithm 2. Improved Harmony Search PTS Algorithm

1: Define *HMS*, *HMCR*, *K*, $PAR_{\min}$, $PAR_{\max}$, $bw_{\min}$, $bw_{\max}$
2: $b_i = b_i^{\min} + rand \in (0,1) \times (b_i^{\max} - b_i^{\min})$, where i = 1, 2:::*HMS*;
3: Calculate the objective function $f(b), b \in \{e^{j\phi_m}\}^M$
4: Define maximum number of iterations (*K*)
5: Initialize *HM*
6: **for** b_i = 1: *HMS* **do**
7: Improvise new *HM*
for *iteration* ≤ *K* **do**
8: **for** $b_i \le$ no. of variable **do**
9: $PAR(k) = PAR_{\min} + \left(\frac{PAR_{\max} - PAR_{\min}}{K}\right)k$
10: $bw(k) = bw_{\max} \exp + \left(\frac{\ln(bw_{\min}/bw_{\max})}{K}\right)k$
11: **for** (all variable) **do**
12: **if** $rand \in (0,1) \le HMCR$ **then**
13: *choose a value from HM*
14: $b_i \in [b_{i,1}, b_{i,2}, \ldots, b_{i,HMS}]$;
15: **if** $rand \in (0,1) \le PAR$ **then**
16: $b_i = b_i^{\min} + rand \in (0,1) \times (b_i^{\max} - b_i^{\min})$,
17: **end if**
18: **end for**
19: **if** new solution ≤ worst solution **then**
20: accept the new harmony and replace the worst in *HM*
21: **end if**
22: **end for**
23: **end for**
24: **end for**
25: *best = best current solution*

IV. Simulation Results and Discussions

To evaluate the performance of the IHS-PTS algorithm for PAPR reduction, various simulations were conducted. To generate the CCDF of the PAPR, 10,000 OFDM symbols with 16-QAM modulation were randomly generated. Next, the transmitted signal was oversampled by a factor of 4 for an accurate PAPR. Figure 2 shows the CCDF vs. PAPR performance of the IHS-PTS system for various modulation schemes, that is, QPSK, 16-QAM, and 64-QAM with $M = 8$, $N = 256$, and $W = 2$. Since the power requirement for the 64-QAM modulation scheme will be higher and proportional to the transmitted data rate in the OFDM system, in this paper, the 16-QAM modulation scheme was considered for the simulation to obtain an optimum data rate and moderate power to the subcarrier.

The performance of IHS-PTS was compared with state-of-the-art techniques, that is, HS-PTS and FF-PTS. For the FF-PTS algorithm, the parameters defined are the number of fireflies = 10, number of iterations = 10, absorption coefficient $\gamma = 1$, attractiveness of firefly $\beta = 0.2$, and randomness $\alpha = 0.5$.

For the HS-PTS algorithm, the parameters are defined as the harmony memory size (HMS) = 16, harmony memory consideration rate ($HMCR$) = 0.95, pitch adjustment rate (PAR) = 0.05, and bandwidth of adjustment (bw) = 0.2. The total number of iterations K is 10. To improve the performance of the algorithm, an improved version of the harmony search algorithm was applied. In this Improved Harmony Search (IHS), PAR and bw are dynamically updated. When this algorithm was used with PTS (IHS-PTS), the PAPR performance improved for the OFDM signal. For a simulation, the minimum and maximum value of the PAR and bandwidth were taken as $PAR_{\min} = 0.3$, $PAR_{\max} = 0.9$, $bw_{\min} = 0.2$, and $bw_{\max} = 0.5$, respectively. Both values were updated by using (16) and (17). When these methods were simulated to optimize the phase factor in the T-PTS method of PAPR reduction, the PAPR decreased in each case.

Figure 3 illustrates the CCDF vs. PAPR performance of a 16-QAM OFDM-PTS system for $M = 4$ subblocks when $N = 256$ and $W = 2$. It can be seen that the PAPR of the original OFDM signal is around 10.7 dB and is reduced to 8.8 dB with a CCDF of 10^{-3} in the case of T-PTS. When FF-PTS is performed, the PAPR is 8.1 dB with a CCDF of 10^{-3}. After applying the HS-PTS and IHS-PTS techniques, the PAPR is around 7.5 dB and 6.9 dB, respectively. Thus, among all three optimization algorithms, IHS-PTS performed very well, and it improves the performance of the OFDM signal.

Next, the same simulation is performed for $M = 8$ and 16 subblocks, which are shown in Figs. 4 and 5,

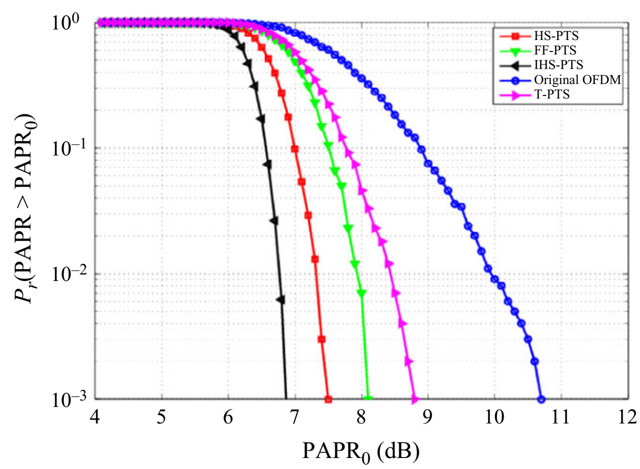

Fig. 3. CCDF vs. PAPR performance of 16-QAM OFDM-PTS system for $M = 4$ subblocks when $N = 256$ and $W = 2$.

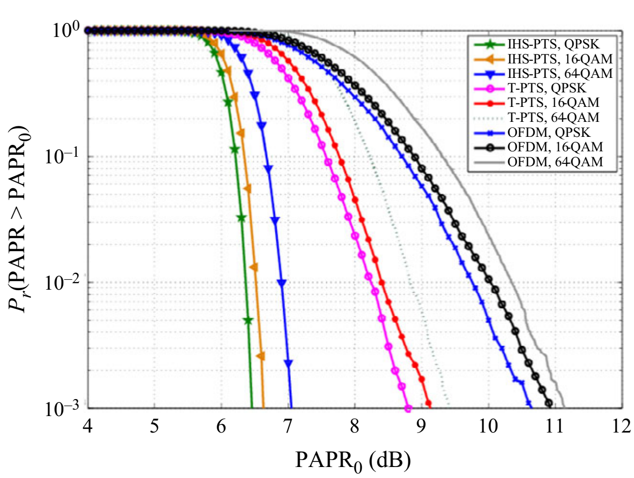

Fig. 2. CCDF vs. PAPR performance of IHS-PTS system for various modulation schemes with $M = 8$, $N = 256$, and $W = 2$.

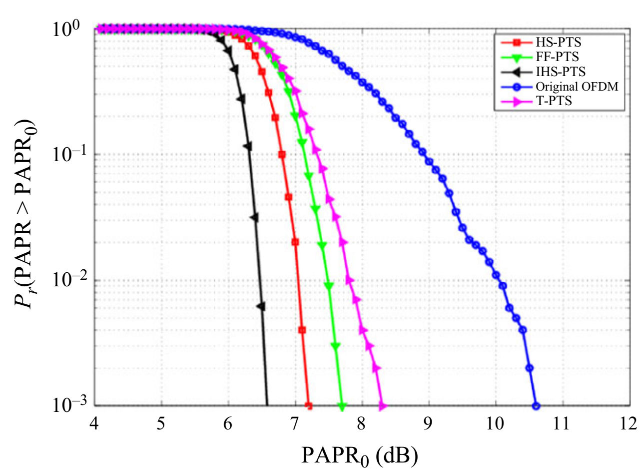

Fig. 4. CCDF vs. PAPR performance of 16-QAM OFDM-PTS system for $M = 8$ subblocks when $N = 256$ and $W = 2$.

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respectively. From simulations, it is evident that the IHS-PTS scheme decreases the PAPR as compared with the HS-PTS and FF-PTS optimization algorithms. For $M = 8$, the PAPR is 8.3 dB after applying PTS. After performing FF-PTS, the PAPR of the OFDM signal is 7.7 dB. When HS-PTS and IHS-PTS are simulated, the PAPR is 7.2 dB and 6.6 dB, respectively.

Similarly, for $M = 16$, the PAPR of T-PTS is around 7.7 dB. When HS-PTS, IHS-PTS, and FF-PTS are performed, the PAPR is 7.1 dB, 6.2 dB, and 7.2 dB, respectively. Thus, by these simulation results, we observe that the IHS-PTS method performed better than the other two optimization methods, that is, FF-PTS and HS-PTS, when the number of subblocks was varied.

Moreover, it can be observed that as the number of subblocks and the set of phase weighting factors is increased, the performance of the PAPR reduction becomes better, but the processing time increases because of the complexity involved.

In Figs. 6, 7, and 8, simulation results of the CCDF vs. PAPR performance of a 16-QAM OFDM-PTS system for various values of subcarriers are shown when $M = 8$ and $W = 2$. Simulations were conducted for the original OFDM, T-PTS, FF-PTS, HS-PTS, and IHS-PTS algorithms. For phase weight factor b, uniformly distributed random variables are used. As we can see, the CCDF of the PAPR is gradually increased upon increasing the number of subcarriers owing to the limited phase weighting factor.

As the numbers of subcarriers are increased, the PAPR improves. In the simulation results, when $N = 128$, $M = 8$, and $W = 2$, the PAPR of the original OFDM signal and T-PTS are 10.0 dB and 7.6 dB, respectively.

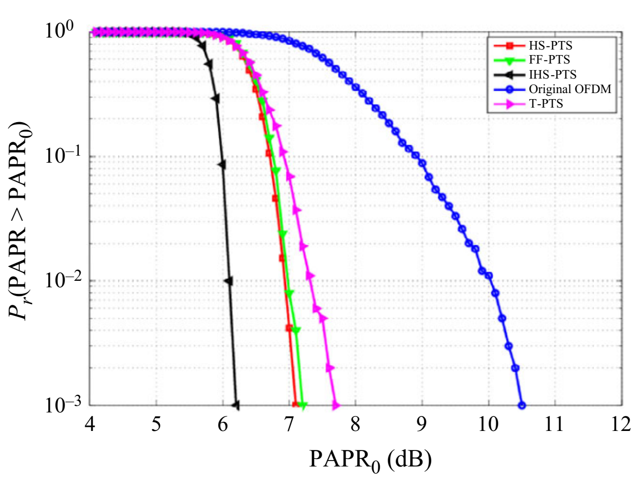

Fig. 5. CCDF vs. PAPR performance of 16-QAM OFDM-PTS system for $M = 16$ subblocks when $N = 256$ and $W = 2$.

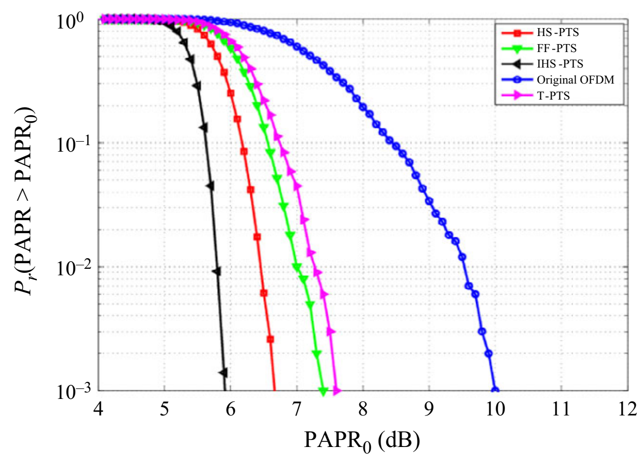

Fig. 6. CCDF vs. PAPR performance of 16-QAM OFDM-PTS system for $N = 128$ subcarriers when $M = 8$ and $W = 2$.

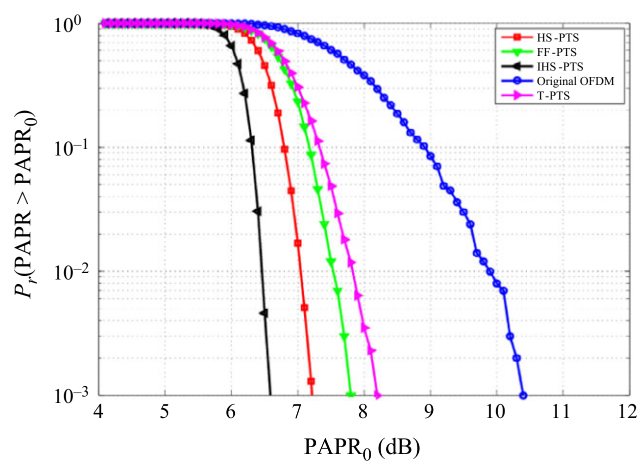

Fig. 7. CCDF vs. PAPR performance of 16-QAM OFDM-PTS system for $N = 256$ subcarriers when $M = 8$ and $W = 2$.

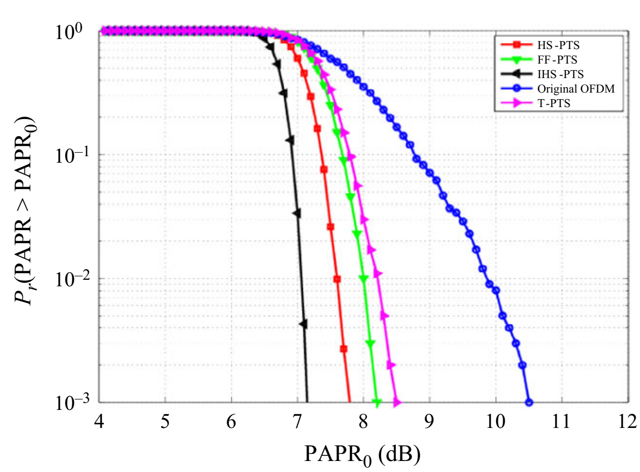

Fig. 8. CCDF vs. PAPR performance of 16-QAM OFDM-PTS system for $N = 512$ subcarriers when $M = 8$ and $W = 2$.

After applying HS-PTS, IHS-PTS, and FF-PTS, the PAPR is 7.8 dB, 7.1 dB, and 8.2 dB, respectively, with a CCDF of 10^{-3}. When $N = 256$, $M = 8$, and $W = 2$, the PAPR of the original OFDM signal and T-PTS are 10.4 dB and 8.2 dB, respectively. After applying HS-PTS, IHS-PTS, and FF-PTS, the PAPR is 7.2 dB, 7.1 dB, and 8.2 dB, respectively, with a CCDF of 10^{-3}. However, with $N = 512$ subcarriers, the PAPR of the original OFDM signal and T-PTS are approximately 10.5 dB and 8.5 dB. The PAPR of the OFDM signal after using HS-PTS, IHS-PTS, and FF-PTS is 7.8 dB, 7.1 dB, and 8.2 dB, respectively, with a CCDF of 10^{-3}. Thus, it is observed that PAPR values are dependent on the number of subcarriers used for OFDM generation. The optimization-algorithm-based PTS shows an improvement in PAPR performance in each case. From the above descriptions, we can see that IHS-PTS is an effective technique for reducing the PAPR of an OFDM system, even with a large number of subcarriers [31].

Figure 9 compares the CCDF vs. PAPR performance of the IHS-PTS technique as a function of various iterations K in a system with 16-QAM modulation, $N = 256$, $M = 8$, and $W = 2$. When the number of iterations K is 10, then the PAPR of the original OFDM signal and T-PTS is 10.6 dB and 8.2 dB, respectively. After applying HS-PTS and IHS-PTS, the PAPR decreased to 7.3 dB and 6.8 dB, respectively. When the number of iterations K was increased to 20, then PAPR of HS-PTS and IHS-PTS was observed to be 7.2 dB and 6.6 dB, respectively.

When simulations were conducted for 40 iterations, the PAPR of HS-PTS and IHSPTS as observed to be 7.1 dB and 6.4 dB, respectively, at a CCDF of 10^{-3}. As the number of iterations was increased, the PAPR improved.

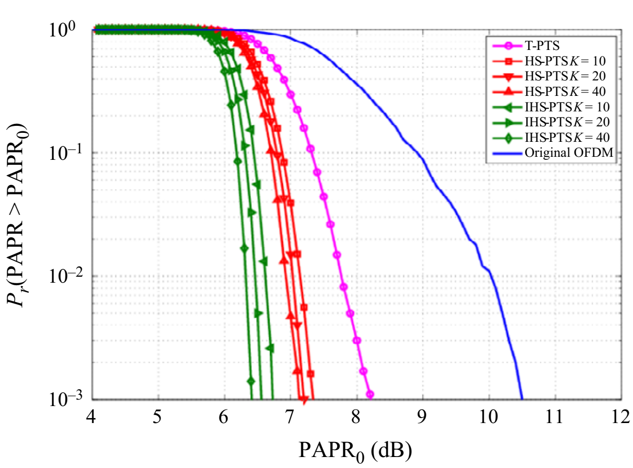

Fig. 9. CCDF vs. PAPR performance of IHS-PTS technique for different iterations when $N = 256$, $M = 8$, $W = 2$, and $HMS = 16$.

However, an increase in the number of iterations increased the processing time, since with a larger number of iterations, the function evaluation leading computation complexity also increases. Hence, it can be seen that the optimization-based PTS schemes deliver desirable trade-offs between the PAPR performance and the computational complexity.

The effect of modulation formats on PAPR was then analyzed for the IHS-PTS algorithm. Figure 10 shows the PAPR performance of the HS-PTS and IHS-PTS schemes for different modulation orders such as QPSK, 8-QAM, 16-QAM, 32-QAM, and 64-QAM. Simulation parameters were taken as $M = 8$ subblocks, $N = 256$ subcarriers, $W = 2$, and $K = 10$ iterations. The population size/generations were considered from 10 to 20 only. It can be seen from the results that IHS-PTS provides a linear performance for different modulation formats. At $G_n = 20$, the PAPR performance of the IHS-PTS scheme was approximately close to that of OPTS, but at the cost of higher complexity. Thus, a trade-off between PAPR performance and complexity calculation in terms of population size is required for implementation.

The summarized results presented in Fig. 11 show the 16-QAM HS-PTS and IHS-PTS performance for different numbers of subcarriers in a range of 32 to 512 when $M = 8$, $W = 2$, and $K = 10$. It can be seen from the graph that the performance of the IHS-PTS scheme was better at lower numbers of generations/population sizes, that is, $G_n = 20$. It is also clear from the results that the performance of the PTS technique degrades with an increase in the number of subcarriers.

A summary of the results is shown in Fig. 12, which compares the performance of the IHS-PTS technique with T-PTS [10], OPTS [24], Tabu-PTS [14], FF-PTS [15], HS-PTS [17], and ABC-PTS [13] with 16-QAM modulation. This implies that the IHS-based PTS

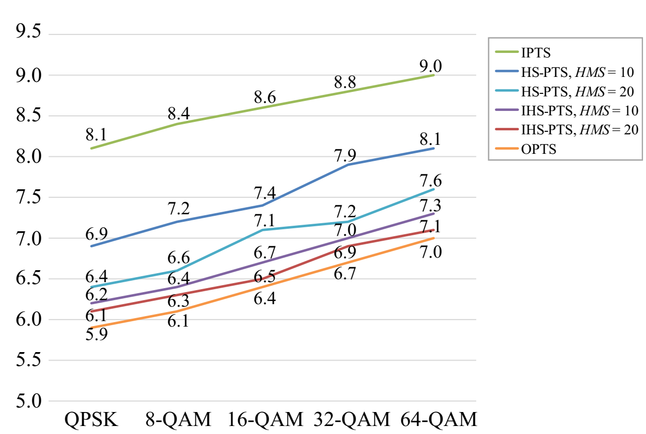

Fig. 10. IHS-PTS performance for different modulation formats.

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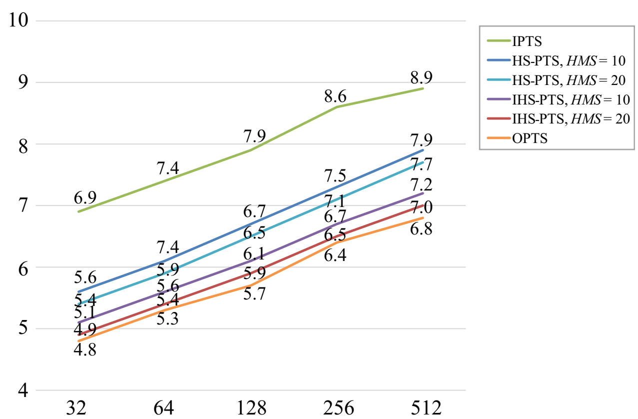

Fig. 11. IHS-PTS performance for different numbers of subcarriers.

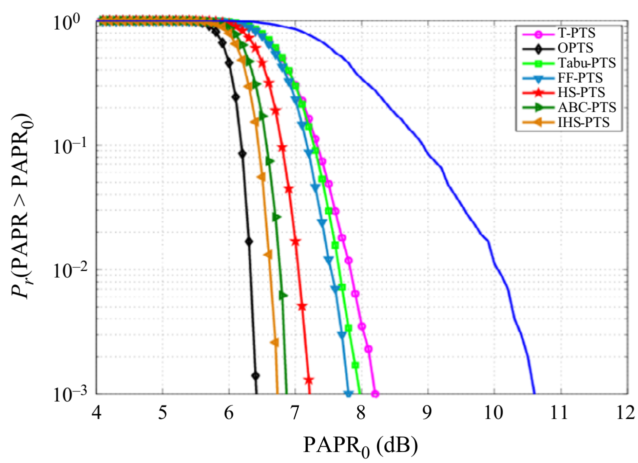

Fig. 12. CCDF vs. PAPR performance comparison of IHS-PTS, HS-PTS, FF-PTS, Tabu-PTS, and ABC-PTS.

technique exhibits better PAPR reduction performance when compared with other existing evolutionary optimization techniques for the same or almost the same search complexity. Simulation results of IHS-PTS are presented with subcarriers of 256 and the same iteration number $K = 10$ where subblocks $M = 8$ are generated by random partition.

The PAPR value of the OPTS method is approximately 6.4 dB for a CCDF of 10^{-3}. The PAPR by the Tabu-PTS with search complexity $M \times W \times K = 16 \times 2 \times 10 = 320$ in [14] is 8.0 dB. By using FF-PTS [15], the PAPR is reduced to 7.8 dB. The PAPR by HS-based PTS with the search complexity $M \times W \times K = 8 \times 2 \times 10 = 160$ is 7.2 dB [17]. Using ABC-PTS with the search complexity $S \times K = 10 \times 10 = 100$ in, the PAPR is reduced to 6.9 dB [13]. From Table 1, it can be clearly seen that apart from the PAPR by OPTS, IHS-PTS provides the best PAPR reduction performance among all methods for the same or almost the same search complexity.

Table 1. CCDF vs. PAPR performance and computational complexity analysis of 16-QAM OFDM PTS system with various optimization techniques.

Methods	Computational complexity	CCDF	PAPR (dB)
OFDM	0	10^{-3}	10.7
T-PTS	$W \times M = 2 \times 16 = 32$	10^{-3}	8.2
TABU-PTS	$M \times W \times K = 16 \times 2 \times 10 = 320$	10^{-3}	8.0
FF-PTS	$G_n \times K = 10 \times 10 = 100$	10^{-3}	7.8
HS-PTS	$M \times W \times K = 8 \times 2 \times 10 = 160$	10^{-3}	7.2
ABC-PTS	$S \times K = 10 \times 10 = 100$	10^{-3}	6.9
IHS-PTS	$M \times W \times K = 8 \times 2 \times 10 = 160$	10^{-3}	6.7
OPTS	$W^{M-1} = 2^{15} = 32{,}768$	10^{-3}	6.4

V. Conclusion

In academia and industry, after the development of smart grid systems and reliable multiuser communication, many researchers have focused more on the PAPR reduction problem for OFDM signals. In this paper, we applied a variant of the harmony search algorithm, that is, an improved harmony-search-based PTS algorithm (IHS-PTS), to search an optimum combination of phase factors for OFDM signals. Compared with PAPR reduction optimization techniques such as the firefly algorithm and the harmony search algorithm, the IHS-PTS algorithm provides improved PAPR owing to its simple structure and very few parameters to adjust for larger PTS subblocks. Simulation results of the IHS-PTS algorithm indicate that it is an efficient and feasible method, and can provide better PAPR performance. Improved PAPR performance using efficient optimization techniques is key to the effectiveness of future wireless high-speed communication systems.

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