

# A PAPR Reduction Method Based on Artificial Bee Colony Algorithm for OFDM Signals

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**Abstract**—One of the major drawbacks of orthogonal frequency division multiplexing (OFDM) signals is the high peak to average power ratio (PAPR) of the transmitted signal. Many PAPR reduction techniques have been proposed in the literature, among which, partial transmit sequence (PTS) technique has been taken considerable investigation. However, PTS technique requires an exhaustive search over all combinations of allowed phase factors, whose complexity increases exponentially with the number of sub-blocks. In this paper, a newly suboptimal method based on modified artificial bee colony (ABC-PTS) algorithm is proposed to search the better combination of phase factors. The ABC-PTS algorithm can significantly reduce the computational complexity for larger PTS subblocks and offers lower PAPR at the same time. Simulation results show that the ABC-PTS algorithm is an efficient method to achieve significant PAPR reduction.

**Index Terms**—PTS, PAPR, OFDM, ABC.

## I. INTRODUCTION

IN various high-speed wireless communication systems, the orthogonal frequency division multiplexing (OFDM) has been used widely due to its inherent robustness against multipath fading and resistance to narrowband interference. Well-known examples include wireless local area network (WLAN) IEEE 802.11a [1] and wireless metropolitan area network (WMAN) IEEE 802.16a [2], digital audio broadcasting (DAB), digital video broadcasting (DVB-T) [3].

However, one of the major drawbacks of OFDM signals is the high peak to average power ratio (PAPR) of the transmitted signal. The high peaks of an OFDM signal occur when the subsymbols for each subcarrier are added up coherently. So OFDM signals can cause serious problems including a severe power penalty at the transmitter which is particularly not affordable in portable wireless systems. Several solutions have been proposed in recent years. It is known that clipping [4] is the simplest method, but it degrades the bit-error-rate (BER) of the system, and results in out-of-band noise and in-band distortion. Although coding [5], [6] can offer the best PAPR

reductions, the associated complexity and data rate reduction limit the application of such a technique. On the other hand, selected mapping (SLM) technique [7] modifies the phases of the original information symbols in each OFDM block and selects the phase-modified OFDM block with the best PAPR performance for transmission. However, the requirement of multiple IFFT operations increases the implementation complexity.

In [8], [9], a tone reservation algorithm has been proposed where several subcarriers are put apart for PAPR reduction. In [9], a tone injection algorithm has been developed where the constellation points of part subcarriers are modified to obtain PAPR reduction at the cost of an increase in transmit power. An active set extension (ASE) algorithm has been proposed in [10], [11]. By modifying the exterior modulation constellation over active subcarriers and not degrading the BER performance, PAPR reduction is achieved. In [12], a symmetric constellation extension (SCE) algorithm has been developed for PAPR reduction, where the subsymbols for each subcarrier are represented by two symmetric constellation points and an optimal representation has been derived by using a derandomization algorithm. In [13], a constellation extension method has been developed, where the data for each subcarrier can be represented by a point in the original constellation or by an extension point. By selecting an optimal representation of the data points, PAPR reduction is obtained. By modifying the modulation constellation or constellation extension, these algorithms require an increase in the transmit power and computation complexity at the transmitter.

The partial transmit sequence (PTS) [14] is a distortionless technique based on combining signal subblocks which are phase-shifted by constant phase factors. The technique can get sufficient PAPR reduction and side information need to be sent at the same time. But the exhaustive search complexity of the optimal phase combination increases exponentially with the number of sub-blocks. So many suboptimal PTS methods have been developed. The iterative flipping algorithm for PTS in [15] has the computational complexity linearly proportional to the number of subblocks. A neighborhood search is proposed in [16] using gradient descent search. A suboptimal method in [17] is developed by modifying the problem into an equivalent problem of minimizing the sum of phase-rotated vectors. A simulated annealing method is proposed in [19]. A suboptimal PTS algorithm based on particle swarm optimization is proposed in [20], [21]. An intelligent genetic algorithm for PAPR reduction is developed in [22], [23].

In this paper, we propose a newly suboptimal phase optimization scheme based on modified artificial bee colony

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(ABC-PTS) algorithm, which can efficiently reduce the PAPR of OFDM signals. The proposed scheme can search the better combination of the initial phase factors. Simulation results show that the ABC-PTS phase optimization scheme can achieve superior PAPR reduction performance and at the same time requires far less computational complexity than the previous PTS techniques. Like the original PTS, our scheme also requires to send side information.

This paper is organized as follows. In Section II, definition of PAPR of OFDM signals and the complementary cumulative distribution function (CCDF) are introduced. The principles of PTS techniques are described in Section III. The modified ABC (ABC-PTS) algorithm to search the better combination of the phase factors is proposed in Section IV. In Section V, the performance of ABC-PTS algorithm and other algorithms for PAPR reduction is evaluated by computer simulation. Conclusions are made in Section VI.

## II. OFDM SYSTEM AND PAPR

In an OFDM system, a high-rate data stream is split into  $N$  low-rate streams that are transmitted simultaneously by subcarriers, where  $N$  is the number of subcarriers. Each of the subcarriers is independently modulated using phase-shift keying (PSK) or quadrature amplitude modulation (QAM). The inverse discrete Fourier transform (IDFT) generates the ready-to-transmit OFDM signal. For an input OFDM block  $\mathbf{X} = [X_0, \dots, X_{N-1}]^T$ , each symbol in  $\mathbf{X}$  modulates one subcarrier of  $\{f_0, \dots, f_{N-1}\}$ . The  $N$  subcarriers are orthogonal, i.e.,  $f_n = n\Delta f$ , where  $\Delta f = 1/NT$  and  $T$  is the symbol period. The complex envelope of the transmitted OFDM signal in one symbol period is given by

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

The PAPR of  $x(t)$  is defined as the ratio of the maximum instantaneous power to the average power, that is

$$PAPR = \frac{\max_{0 \leq t < NT} |x(t)|^2}{E[|x(t)|^2]}, \quad (2)$$

where

$$E[|x(t)|^2] = 1/NT \int_0^{NT} |x(t)|^2 dt. \quad (3)$$

However, most systems use discrete-time signals in which the OFDM signal is expressed as

$$x(k) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} X_n \cdot e^{j\frac{2\pi nk}{LN}}, k = 0, 1, \dots, LN - 1, \quad (4)$$

where  $L$  is the oversampled factor. It has been shown in [18] that the oversampled factor  $L = 4$  is enough to provide a sufficiently accurate estimate of the PAPR of OFDM signals.

The complementary cumulative distribution function (CCDF) is one of the most frequently used performance measures for PAPR reduction, representing the probability that the PAPR of an OFDM symbol exceeds the given threshold  $PAPR_0$ , which is denoted as

$$CCDF = Pr(PAPR > PAPR_0). \quad (5)$$

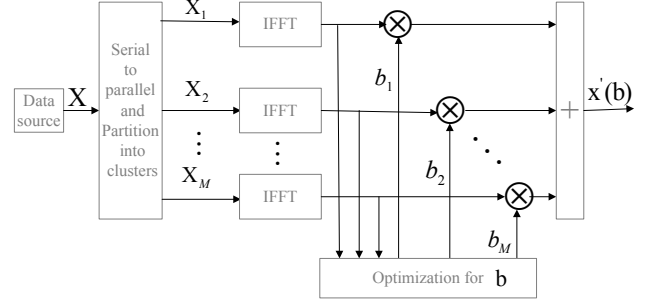


Fig. 1. Block diagram of the PTS technique.

## III. PTS TECHNIQUES

The principle structure of PTS method is shown in Fig. 1. The input data block  $\mathbf{X}$  is partitioned into  $M$  disjoint sub-blocks  $\mathbf{X}_m, m = 1, 2, \dots, M$  such that  $\mathbf{X} = \sum_{m=1}^M \mathbf{X}_m$ . Sub-blocks are combined to minimize the PAPR in the time domain.  $L$ -times oversampled time domain signal of  $\mathbf{X}_m$  is denoted as  $\mathbf{x}_m, m = 1, 2, \dots, M$ , which are obtained by taking an IDFT of length  $NL$  on  $\mathbf{X}_m$  concatenated with  $(L-1)N$  zeros. Each  $\mathbf{x}_m$  is multiplied by a phase weighting factor  $b_m = e^{j\phi_m}$ , where  $\phi_m \in [0, 2\pi)$  for  $m = 1, 2, \dots, M$ . The goal of the PTS approach is to find an optimal phase weighted combination to minimize the PAPR value. The transmitted signal in the time domain after combination can be expressed as

$$\mathbf{x}'(\mathbf{b}) = \sum_{i=1}^M b_i \mathbf{x}_i, \quad (6)$$

where  $\mathbf{x}'(\mathbf{b}) = [x'_1(\mathbf{b}), x'_2(\mathbf{b}), \dots, x'_{NL}(\mathbf{b})]$ .

In general, the selection of the phase factor is limited to a set with finite number of elements to reduce the search complexity. The set of allowed phase factors is

$$\mathbf{P} = \{e^{j2\pi\ell/W} | \ell = 0, 1, \dots, W-1\}. \quad (7)$$

where  $W$  is the number of allowed phase factors. We can fix a phase factor without any performance loss. There are only  $M-1$  free variables to be optimized and hence  $W^{M-1}$  different phase vectors are searched to find the global optimal phase factor. The search complexity increases exponentially with  $M$ , the number of sub-blocks.

## IV. MINIMIZE PAPR USING MODIFIED ABC ALGORITHM

In order to get the OFDM signals with the minimum PAPR, a suboptimal combination method based on the modified artificial bee colony (ABC) algorithm is proposed to solve the optimization problem of PTS. The modified ABC algorithm with lower complexity can get better PAPR performance.

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

Minimize

$$f(\mathbf{b}) = \frac{\max |x'(\mathbf{b})|^2}{E[|x'(\mathbf{b})|^2]}, \quad (8)$$

subject to

$$\mathbf{b} \in \{e^{j\phi_m}\}^M, \quad (9)$$

where  $\phi_m \in \{\frac{2\pi k}{W} | k = 0, 1, \dots, W-1\}$ .

### A. Artificial Bee Colony Algorithm

In recent years, Karaboga *et al* [24]–[26] introduced a bee swarm algorithm called artificial bee colony (ABC) algorithm for numerical optimization problems. In the ABC algorithm, the colony of artificial bees contains three groups of bees: employed bees, onlookers and scouts. Each cycle of the search consists of three steps: (1) placing the employed bees onto the food sources and then calculating their nectar amounts; (2) selecting the food sources by the onlookers after sharing the information of employed bees and determining the nectar amount of the foods; (3) determining the scout bees and placing them onto the randomly determined food sources. In the ABC, a food source position represents a possible solution to the problem to be optimized and the nectar amount of a food source corresponds to the quality (fitness) of the associated solution.

At the initialization step, a set of food source positions are randomly produced and corresponding nectar amounts are calculated. Each employed bee is moved onto her food source area for determining a new food source within the neighbourhood of the present one, and then its nectar amount is evaluated. If the nectar amount of the new one is higher than that of the previous one, she memorizes the new position and forgets the old one. Otherwise she keeps the position of the previous one. After all employed bees complete the search process, they come back into the hive and share the nectar information of the food sources (solutions) and their position information with the onlooker bees waiting on the dance area. All onlookers determine a food source area with a probability based on their nectar amounts. If the nectar amount of a food source is much higher when compared with other food sources, this means that this source will be chosen by most of the onlookers. Each onlooker determines a neighbourhood food source within the neighbourhood of the one to which she has been assigned and then its nectar amount is evaluated. The selection of the scout bee is controlled by a control parameter called “limit”. If a solution representing a food source cannot be improved by a predetermined number of trials, i.e., “limit”, it means that the associated food source has been exhausted by the bees and then the employed bee of this food source becomes a scout. The position of the abandoned food source is replaced with a randomly produced food position. So “limit” controls the selection of the scout bee and the qualities of solutions. These three steps are repeated until the termination criteria are satisfied. For a complete understanding of the ABC method, the reader is referred to [24]–[26].

### B. Modified Artificial Bee Colony Algorithm to Reduce PAPR

Due to the facts that the original ABC algorithm is only suitable for continuously numerical optimization problems, we have to do some modifications for the original ABC algorithm in order to apply ABC algorithm to search the better combination of phase factors for PTS. We refer to the modified ABC algorithm as ABC-PTS. In the paper, we select the phase factor  $\mathbf{b} = \{-1, 1\}^M$  or  $\mathbf{b} = \{-1, 1, j, -j\}^M$ .

In the ABC-PTS algorithm, a food source position represents a phase vector  $\mathbf{b}_i = [b_{i1}, b_{i2}, \dots, b_{iM}]^T$ ,  $i =$

$1, 2, \dots, S$ , where  $S$  denotes the size of a randomly distributed initial population. The nectar amount of a food source or fitness value of a solution  $\mathbf{b}_i$  in the population is determined by the following formula:

$$fitness(\mathbf{b}_i) = \frac{1}{1 + f(\mathbf{b}_i)}. \quad (10)$$

For each employed bee, a candidate food source position from the previous one is produced by the following formula:

$$b'_{il} = b_{il} + \phi_{il}(b_{il} - b_{kl}), \quad (11)$$

where  $l \in \{1, 2, \dots, M\}$  and  $k \in \{1, 2, \dots, J\}$ ,  $i \neq k$ ,  $J$  is the number of employed bees (the number of food sources), and  $\phi_{il}$  is a random number between  $[-1, 1]$ . Due to  $b'_{il}$  is the discrete coordinate, thus (11) is modified to the following formulas:

For  $W = 2$

$$b'_{il} = \begin{cases} 1, & \text{if } \pi/4 \leq b'_{il} < 5\pi/4, \\ -1, & \text{else,} \end{cases} \quad (12)$$

For  $W = 4$

$$b'_{il} = \begin{cases} j, & \text{if } \pi/4 \leq b'_{il} < 3\pi/4, \\ -1, & \text{if } 3\pi/4 \leq b'_{il} < 5\pi/4, \\ -j, & \text{if } 5\pi/4 \leq b'_{il} < 7\pi/4, \\ 1, & \text{else,} \end{cases} \quad (13)$$

For each onlooker bee, a food source is chosen depending on the probability value associated with that food source,  $p_i$ , calculated by the following formula:

$$p_i = \frac{fitness(\mathbf{b}_i)}{\sum_{i=1}^S fitness(\mathbf{b}_i)}. \quad (14)$$

After all onlookers are distributed onto the food sources and their nectars are tested, sources are checked whether they are to be abandoned. If the number of cycles that a source can not be improved is greater than a predetermined limit, the source is considered to be exhausted. The employed bee associated with the exhausted source becomes a scout and makes a random search in problem domain by the following formula:

$$b_{il} = b_i^{min} + (b_i^{max} - b_i^{min}) * rand, \quad (15)$$

Our proposed modified ABC algorithm for PAPR reduction (ABC-PTS) can thus be summarized as follows.

- 1) Initialize food source positions, set the value of limit and the maximum iteration number.
- 2) Determine neighbour food source positions for the employed bees using (11). Then modify food source positions using (12) or (13).
- 3) Calculate the nectar amounts or fitness using (10).
- 4) If all onlookers are assigned food sources, go to Step 7. Otherwise, continue.
- 5) Select a food source for an onlooker using (14).
- 6) Determine a neighbour food source position for the onlooker using (11). Then modify food source positions using (12) or (13). Go to Step 4.
- 7) Find the abandoned food source and allocate its employed bee as scout for searching new food sources using (15)

- 8) Memorize the position of the best food source.
- 9) If the maximum iteration number is reached, output final food source positions and stop. Otherwise go to Step 2.

### C. Complexity Analysis for ABC-PTS and the Existing PAPR Reduction Methods

In [15], the iterative flipping algorithm for PTS (IPTS) was proposed for PAPR reduction. The method has the computational complexity linearly proportional to the number of subblocks, i.e. the search complexity is proportional to  $(M-1)W$ . A neighborhood search using gradient descent search (GD) is proposed in [16]. The technique first sets the initial phase factor  $\mathbf{b} = [1, 1, \dots, 1]$  and the number of maximum iteration  $I$ , then searches the phase factor that achieves the smallest PAPR in the neighbour of  $\mathbf{b}$  with radius  $r$ . The search complexity of this method is proportional to  $C_{M-1}^r W^r I$ , where  $C_n^m$  is the binomial coefficient. A suboptimal method (TS) in [17] is developed by modifying the problem into an equivalent problem of minimizing the sum of phase-rotated vectors. The phase factor of the method is continuously changed in  $[0, 2\pi]$ . The search complexity of this method is proportional to  $LN$ , where  $N$  is the number of subcarrier and  $L$  is the oversampled factor. In [20], [21], a particle swarm optimization algorithm (PSO-PTS) is proposed to reduce PAPR. The search complexity of this method is proportional to  $SG$ , where  $S$  is the size of particle swarm,  $G$  is the maximal generations of PSO-PTS. An intelligent genetic algorithm (GA) called minimum distance guided GA (MDGA) is developed in [22], [23]. The MDGA generates initial population by using the output of the IPTS, perturbing the output of the IPTS with minimum Hamming Distance and mutating the output of the IPTS randomly. Then MDGA search the phase factor by an intelligent replacement strategy, crossover and mutation. The search complexity of this method is proportional to  $PG + (M-1)W$ , where  $P$  is the size of the population,  $G$  is the maximal generations of MDGA. In the ABC-PTS algorithm, the randomly initial phase factor population with the size  $S$  are produced, then all employed bees and onlookers carry out search according to the algorithm, when the maximum iteration number  $K$  is reached, the phase factor with the minimum PAPR is thought as the approximately optimal one. So the search complexity of this method is proportional to  $SK$ . The complexity of the PTS technique with an exhaustive search (OPTS) [14] is  $W^{M-1}$  by fixing a phase factor without any performance loss.

## V. SIMULATION RESULTS

To evaluate and compare the performance of the ABC-PTS algorithm for OFDM PAPR reduction, numerous simulations have been conducted. In order to get CCDF, 100000 random OFDM symbols are generated. The transmitted signal is oversampled by a factor of  $L = 4$  for accurate PAPR. In our simulation, 16-QAM modulation with  $N = 256$  sub-carriers is used and the phase factor  $W = 2$  is chosen. When larger phase factor, for example,  $W = 4$  is chosen, the similar simulation results can be obtained, while the performance will be better.

In the ABC-PTS algorithm, there are three control parameters: the number of the food sources, the value of limit and

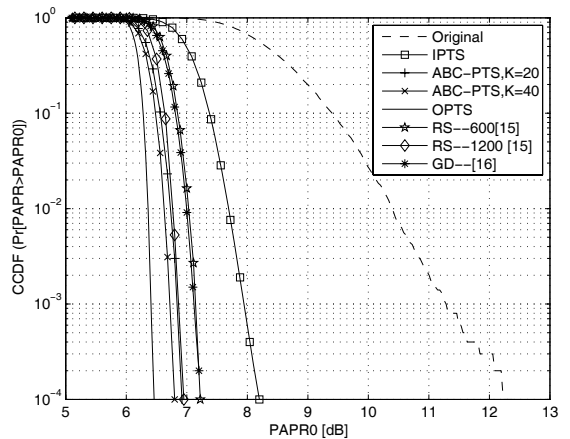


Fig. 2. Comparison of PAPR reduction among ABC-PTS with different iterations and the other methods,  $W=2$ .

the maximum iteration number. Employed bees or onlooker bees carry out the exploiting process in the search space, the scouts control the exploration process in the ABC-PTS algorithm. The two processes are implemented together. Different maximum iteration number, different size of population and different limit value are chosen to evaluate the performance of the ABC-PTS algorithm for PAPR reduction. In simulation,  $S$  denotes the number of the food sources or the size of population,  $K$  denotes the maximum iteration number,  $Limit$  denotes the value of limit.

In Fig. 2, the CCDF for  $M = 16$  sub-blocks using random partition is shown. Here  $S = 30$ ,  $Limit = 5$  and different iteration  $K = 20$ ,  $K = 40$  for the ABC-PTS. When  $P_r(PAPR > PAPR_0) = 10^{-3}$ , the PAPR of the original OFDM is 11.3 dB. The PAPR by IPTS is 7.95 dB. The PAPR by the ABC-PTSs with iteration number 20 and 40 are approximately 6.75 dB and 6.65 dB respectively. Using the random search (RS) in [15], when the numbers of randomly selected phase factors are 600 and 1200, the PAPRs are reduced to 7.15 dB and 6.8 dB respectively. The PAPR by the gradient descent search (GD) with the search complexity  $C_{M-1}^r W^r I = C_{15}^2 2^2 3 = 1260$  in [16] is 7.1 dB. The PAPR by the OPTS with exhaustive search number  $2^{15} = 32768$  is 6.4 dB. There is a 0.25 dB gap between the PAPR by OPTS and by ABC-PTS with iteration number  $K = 40$ . But from the analysis in Section IV-C, we can know that the search complexity of the ABC-PTS with  $K = 40$  is only  $SK/W^{(M-1)} = 1200/32768 = 3.66\%$  of that by the OPTS. For the same or almost same search complexity, the performance of the ABC-PTS with  $K = 40$  is also better than that of RS and GD.

Table I shows comparison of computational complexity among different methods for  $M = 16$  subblocks, where the size of population for PSO-PTS [20], [21], MDGA [22], [23] and ABC-PTS are  $S = P = 30$ , the number of maximal generations or iterations are  $G = K = 30$ . It can be seen that the performance of swarm intelligence algorithms, i.e. PSO-PTS, MDGA and ABC-PTS excel that of other methods. For the same search complexity, the PAPR of the ABC-PTS is smaller 0.3 dB than that of PSO-PTS. For the almost same

TABLE I

WHEN  $CCDF = 10^{-3}$ , COMPARISON OF COMPUTATIONAL COMPLEXITY AMONG DIFFERENT METHODS FOR PHASE FACTOR  $W = 2$ ,  $M = 16$  SUB-BLOCKS, SIZE OF POPULATION/PARTICLE  $P = S = 30$  AND MAXIMAL GENERATIONS/ITERATIONS  $G = K = 30$

methods	computational complexity	PAPR
IPTS	$(M - 1)W = 15 * 2 = 30$	7.95 dB
GD	$C_{M-1}^r W^r I = C_{15}^2 2^2 3 = 1260$	7.15 dB
TS	$LN = 4 * 256 = 1024$	7.25 dB
PSO-PTS	$SG = 30 * 30 = 900$	7.1 dB
MDGA	$PG + (M - 1)W = 30 * 30 + 15 * 2 = 930$	7.0 dB
ABC-PTS	$SK = 30 * 30 = 900$	6.8 dB
OPTS	$W^{M-1} = 2^{15} = 32768$	6.45 dB

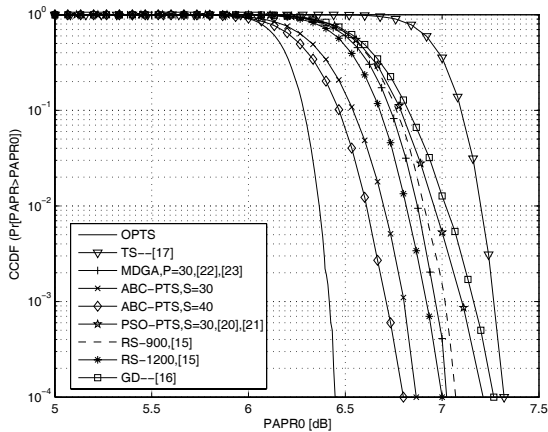


Fig. 3. Comparison of PAPR reduction among ABC-PTS with different size of population and the other methods,  $W=2$ .

search complexity, the PAPR of the ABC-PTS is smaller 0.2 dB than that of MDGA.

In Fig. 3, we compare the PAPR reduction performance of the ABC-PTS with the other methods in [15]–[17], [20]–[23] for the same or almost same search complexity. Fig. 3 shows the simulation results of the ABC-PTS with different size of population, the same maximum iteration number  $K = 30$  and  $Limit = 5$ , where subblocks  $M = 16$  are generated by random partition. When  $P_r(PAPR > PAPR_0) = 10^{-3}$ , the PAPR by OPTS is approximately 6.45 dB. By using the ABC-PTS with  $S = 30$  and  $S = 40$ , the PAPRs are reduced to 6.8 dB and 6.7 dB, respectively. Compared to the PAPR by OPTS, the PAPR by the ABC-PTS with  $S = 30$  and  $S = 40$  has a gap approximately 0.35 dB and 0.25 dB, respectively. But the search complexity of the ABC-PTS is only 2.75% and 3.66% of that by the OPTS, respectively. Using RS in [15], when the numbers of randomly selected phase factors are 900 and 1200, the PAPRs are reduced to 7 dB and 6.9 dB, respectively. The PAPR by GD with the search complexity  $C_{M-1}^r W^r I = C_{15}^2 2^2 3 = 1260$  in [16] is 7.15 dB. The PAPR by TS with the search complexity  $LN = 4 * 256 = 1024$  in [17] is 7.3 dB. Using the MDGA with the search complexity  $PG + (M - 1)W = 30 * 30 + 15 * 2 = 930$  in [22], [23], the PAPR is reduced to 6.95 dB. The PAPR by the PSO-PTS with the search complexity  $SG = 30 * 30 = 900$  in [20], [21] is 7.1 dB. From Fig. 3, it can be seen that apart from the PAPR

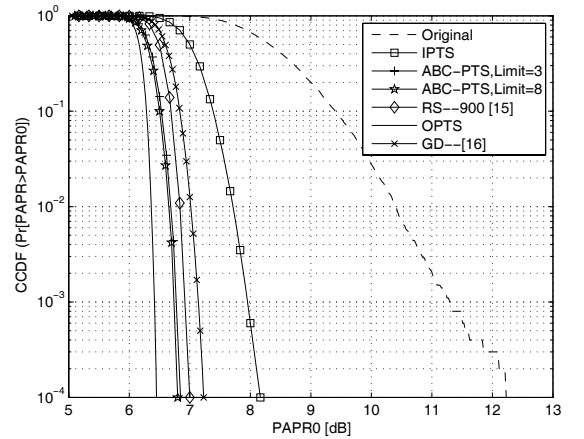


Fig. 4. Comparison of PAPR reduction among ABC-PTS with different Limit and the other methods,  $W=2$ .

by OPTS, the PAPR reduction performance of the ABC-PTS is the best among that of all methods for the same or almost same search complexity.

In Fig. 4, we compare the PAPR reduction performance of the ABC-PTS with different Limit, the same size of population  $S = 30$  and the same maximum iteration number  $K = 30$  for  $M = 16$  sub-blocks. When  $P_r(PAPR > PAPR_0) = 10^{-3}$ , the PAPR of the original OFDM is 11.3 dB, the PAPRs by the ABC-PTS with  $Limit = 3$  and  $Limit = 8$  are 6.8 dB and 6.8 dB respectively. The PAPR by the OPTS is 6.5 dB. The PAPR by IPTS is 7.95 dB. The PAPR by RS [15] with 900 randomly selected phase factors is 6.95 dB. The PAPR by GD [16] is 7.1 dB. From Fig. 4, it can be discovered that the difference of the PAPR between  $Limit = 3$  and  $Limit = 8$  is negligible. Little performance improvement can be obtained by increasing Limit.

For three swarm intelligence algorithms, i.e. the PSO-PTS [20], [21], the MDGA [22], [23] and the ABC-PTS, 100 experiments are performed to compare PAPR convergence performance for an OFDM symbol, where subblocks  $M = 16$  are generated by random partition, the same size of population is  $S = P = 30$  and the same maximum iteration number  $G = K = 60$ . Fig. 5 shows the simulation results of three different methods on the mean of the best cost function values. In initial phase (approximately 1 – 3 iterations), the performance of the ABC-PTS is inferior to that of PSO-PTS and MDGA. As the increase of iterations, the performance of the ABC-PTS is better than that of PSO-PTS and MDGA. Although the PAPR performance is improved with the increase of iteration number, the mean of PAPR getting by the iteration number  $K = 30$  is only less 0.1 dB than that of PAPR getting by the iteration number  $K = 60$ , so iteration number  $K = 30$  can be a suitable choice for our proposed ABC-PTS algorithm.

## VI. CONCLUSION

In this paper, we propose a modified ABC based PTS algorithm (ABC-PTS) to search better combination of phase factors for OFDM signals. Compared to the existing PAPR reduction methods, the ABC-PTS algorithm can get better PAPR reduction and significantly reduce the computational

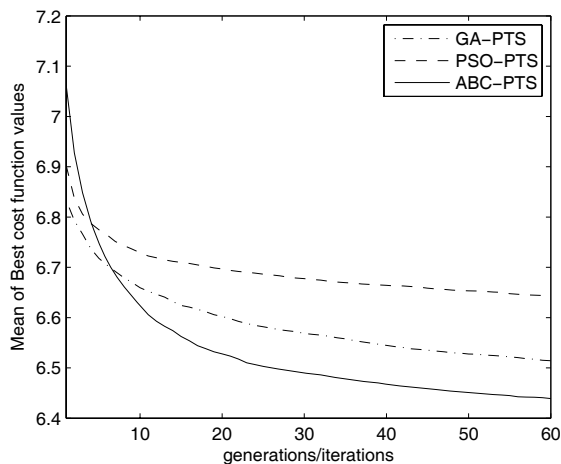


Fig. 5. Comparison of mean of best cost function values for different swarm intelligence methods.

complexity for larger PTS subblocks at the same time. Moreover, because the ABC-PTS algorithm only has three control parameters, so it is easy to be adjusted. Simulation results show that the ABC-PTS algorithm is an efficient method which can provide a better PAPR performance.

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