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A Comparison Study of PAPR Reduction in OFDM Systems Based on Swarm Intelligence Algorithms

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Abstract

Optimization algorithms have been one of the most important research topics in Computational Intelligence Community. They are widely utilized mathematical functions that solve optimization problems in a variety of purposes via the maximization or minimization of a function. The swarm intelligence (SI) optimization algorithms are an active branch of Evolutionary Computation, they are increasingly becoming one of the hottest and most important paradigms, several algorithms were proposed for tackling optimization problems. The most respected and popular SI algorithms are Ant colony optimization (ACO) and particle swarm optimization (PSO). Fireworks Algorithm (FWA) is a novel swarm intelligence algorithm, which seems effective at finding a good enough solution of a complex optimization problem. In this chapter we proposed a comparison study to reduce the high PAPR (Peak-to-Average Power Ratio) in OFDM systems based on the swarm intelligence algorithms like simulated annealing (SA), particle swarm optimization (PSO), fireworks algorithm (FWA), and genetic algorithm (GA). It turns out from the results that some algorithms find a good enough solutions and clearly outperform the others candidates in both convergence speed and global solution accuracy.

Keywords: OFDM, PAPR, PTS, Swarm Intelligence, Fireworks Algorithm, GA, PSO

1. Introduction

In the last decade, Swarm Intelligence (SI) optimization algorithms attracted a great deal of attention and become popular among researchers from different fields and diverse domains working on optimization problems all over the world [1, 2]. The SI methods are increasingly becoming one of the most important research topics of evolutionary computation (EC).

In the past several years, fruitful achievements have been made in the Computational Intelligence researches areas, such as evolutionary computation [3–5], simulated annealing [6], artificial neural networks [7–9], tabu search [10], chaos computation [11], fuzzy logic and systems [12]. All these methods inspired by natural Behavior.

In general, swarm intelligence algorithms (SI) can be divided into two main categories, bio-inspired and non-bio-inspired. The first one includes particle swarm optimization (PSO) [13], ant colony optimization (ACO) [14], artificial bee algorithm (ABC) [15, 16], fish schooling search (FSS) [17], bacterial foraging optimization (BFO) [18], firefly algorithm-II [19], bat algorithm [20] and so forth. The second categories of non-bio-inspired algorithms includes fireworks algorithm (FWA) [21], brain storm optimization (BSO) [22], magnetic optimization algorithms [23] and water drops algorithm [24]. Each algorithm has some advantages in solving many optimization problems but among all these algorithms, PSO, FWA and GA [25, 26] are the most popular algorithms for searching optimal locations in a D-dimensional space.

This chapter aims to present a comparison study to resolve an optimization problem in orthogonal frequency division multiplexing (OFDM) system based on the important evolutionary algorithm in the literature.

The multicarrier modulation techniques like OFDM [27–29] provides a viable alternative to enhance the quality of service for data transmission over single carrier systems, it has various advantages and now being used in a number of wireless communication systems. However, the OFDM system still suffers from the high envelope fluctuations of the transmitted signal called the peak-to-average power ratio (PAPR). This main concern improves the complexity of nonlinear elements, decreases the efficiency of high power amplifiers (HPA), and causes out-of-band radiation with degradation of bit error rate (BER).

Partial transmit sequences (PTS) [30–32] is one of the most attractive technique and a promising scheme due to its efficiency in PAPR reduction, but it requires an exhaustive search to find the optimum phase factors, which causes high computational complexity increased with the number of phase and subblocks. In this paper we will try to present many novel algorithms and their efficient improvements combined with PTS scheme to reduce the PAPR and the computational complexity.

The rest of the chapter is organized as follows. In Section 2, OFDM system model and the PAPR problem is formulated, and then the principles of PTS techniques are introduced. In Section 3, we have introduced the paradigm of Swarm Intelligence algorithms, and outlined the technical details of some popular SI algorithms like FWA, PSO, and GA. We also discuss the characteristics, the framework of the FWA based PTS and some simulation results under this Section. while Sections 4 and 5 are devoted to the comparison study of computational complexity and conclusions successively.

2. Multicarrier modulation (OFDM) and PTS approach

2.1 PAPR in OFDM signal

Wireless communications systems have experienced explosive growth with the demand for high data rate, these digital systems require each channel to operate at a specific frequency and with a specific bandwidth. OFDM systems are currently being implemented in some of the newest and most advanced communications systems due to its effectiveness in using the frequency spectrum. OFDM is a subset of frequency division multiplexing in which a single channel utilizes multiple sub-carriers on adjacent frequencies, this typical technique divides the effective spectrum channel to a number of orthogonal sub-channels and with equal bandwidth, each sub-channel handles independently with its own data using individual subcarrier and the OFDM signal is the sum of all independent subcarriers. As a result, OFDM systems are able to maximize spectral efficiency without causing adjacent channel interference. OFDM signal generated by mapped the input data of binary sequences into complex data

symbols called constellation, by a modulator (PSK, QPSK, QAM, etc.). Then, after serial to parallel conversion, N mapped symbols $\mathbf{X} = [X_0, X_1, \dots, X_{N-1}]^T$ are fed to IDFT block to formed the time domain OFDM signal $\mathbf{x} = [x_0, x_1, \dots, x_{N-1}]^T$. In the discrete time domain and with oversampled factor $L = 4$ The mathematical expression of the complex envelope of OFDM signal can be written as

$$x[n] = \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} X_k e^{j \frac{2\pi n k}{LN}}, 0 \leq n \leq LN - 1 \tag{1}$$

where N is the number of subcarriers and X_k is the n^{th} complex symbol carried and transmitted by the k^{th} subcarrier.

In the time domain, the transmit signals in an OFDM system can have high peak values since many subcarrier components are added via an inverse fast Fourier transformation (IFFT) operation. Compared to single-carrier systems, OFDM systems are known to have a high peak-to-average power ratio (PAPR), which decreases the signal-to-quantization noise ratio (SQNR) of the digital-analog convertor (DAC) and analog-digital convertor (ADC) while degrading the efficiency of the high power amplifier (HPA) in the transmitter.

The PAPR of a signal in discrete time is defined as the ratio between the maximum power and the average power of the complex OFDM signal, it can be expressed by the following formula [29]:

$$\text{PAPR}\{x[n]\} = \frac{\max \left\{ |x[n]|^2 \right\}}{E \left\{ |x[n]|^2 \right\}}, 0 \leq n \leq LN - 1 \tag{2}$$

where $x[n]$ is given by (Eq. (1)) and $E \{.\}$ denotes the expected value (Average power).

2.2 Partial transmit sequence (PTS)

When The PAPR reduction technique of Partial Transmit Sequence (PTS), was proposed in the framework of the continuity of the “Selective Mapping” technique [33]. It is based on the same principle as the SLM, with a multiple representation of the signal. The basic idea of this method has been described and detailed by S.H Muller and J.B Huber in [31, 34]. It consists in partitioning an input data block of N subcarriers into V subblocks of the same size with N/V subcarriers per each subblock. Each subcarrier allocated to the data transmitted in one sub-block will be set to zero in all others.

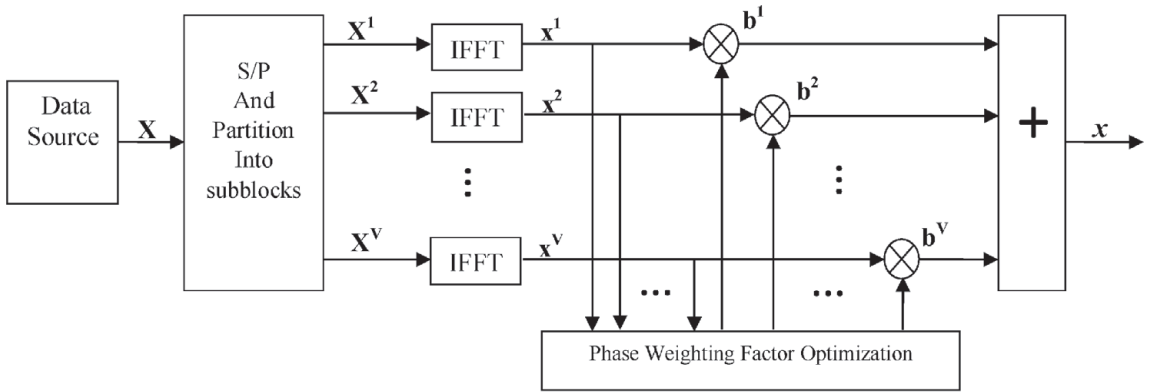


Figure 1.
Block diagram of PTS technique.

Once the V sub-blocks have been formed, the PTS technique applies a phase rotation optimization on each v sub block after IDFT to form the final signal at the lowest PAPR **Figure 1**.

The principle of the PTS technique is illustrated in **Figure 1**, where the algorithm is described as follows:

i. Firstly, after digital modulation, the symbols are subdivided into V sub-blocks, of equal size, such that the original signal is $X = \sum_{v=1}^V X^v$

ii. A phase shift is applied to all data symbols in each independent disjoint sub-block X^v and the new frequency OFDM symbol is written as:

$$X = \sum_{v=1}^V X^v \cdot b^v, b^v = e^{j\phi^v}, v = 1, 2, \dots, V. \quad (3)$$

iii. Subsequently, IFFT is applied on each sub-block to determine the modified OFDM symbol in the time domain.

$$x = IFFT \left\{ \sum_{v=1}^V b^v X^v \right\} = \sum_{v=1}^V b^v \cdot IFFT \{X^v\} = \sum_{v=1}^V b^v x^v, \quad (4)$$

where the phase vector b^v is chosen so that the PAPR can be minimized. It is optimized as follows:

$$[b^1, \dots, b^V] = \arg \min_{[b^1, \dots, b^V]} \left(\max_{n=0,1,\dots,N-1} \left| \sum_{v=1}^V b^v x^v[n] \right| \right) \quad (5)$$

In the practical application of wireless communication systems using the PTS approach, several drawbacks influence the performance of the PTS technique and

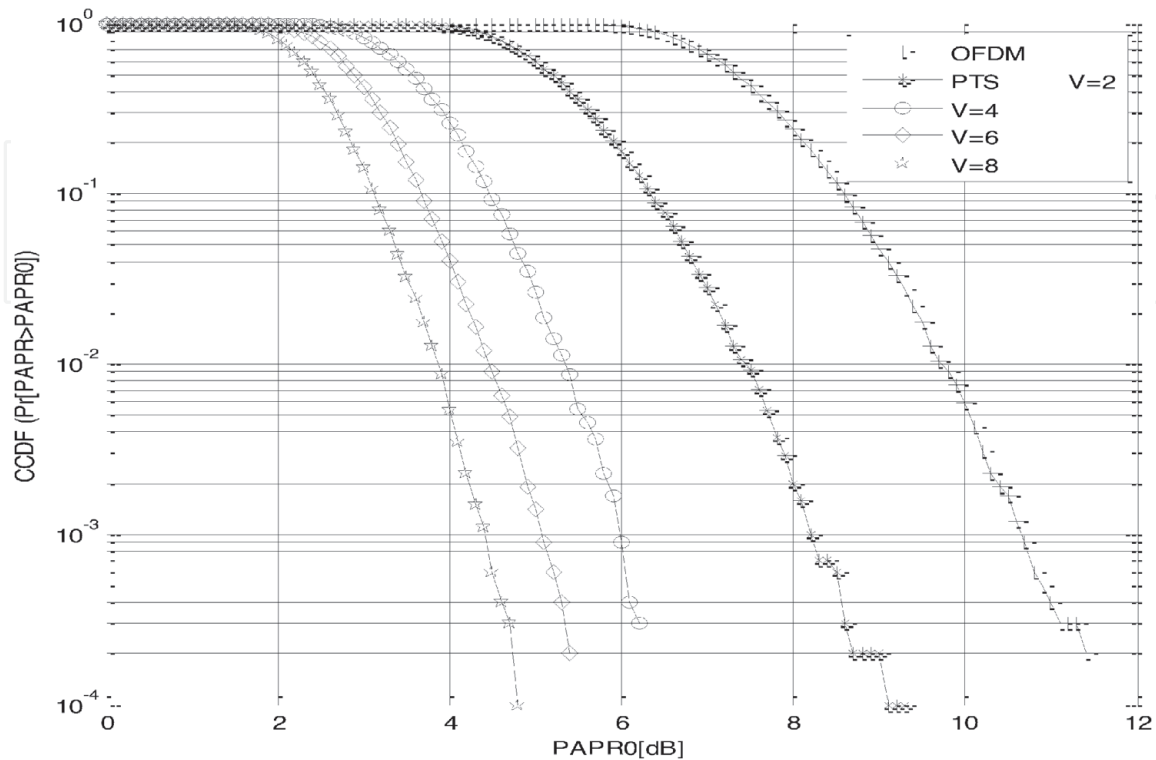


Figure 2.
PAPR reduction performance of PTS-OFDM when the number of sub-blocks varies.

increase its complexity. The PAPR performance will be improved as the number of subblocks V is increased (**Figure 2**). However, the complexity of the system also increased, to match the optimal phase weighting sequence for each input data sequence, W^V possible combinations should be checked (W number of phase factors). Moreover, the PTS technique requires the transmission of “Side Information” (SI) so that the receiver can identify the sequence that generated the lowest PAPR.

Figure 2 is an example of the PAPR for an OFDM signal with 64 subcarriers (802.11a), using a QPSK modulation and OFDM with PTS technique. From the above figure, the PTS method improves the PAPR performance as the number of sub-blocks increases. Several works aiming at complexity reduction, and several optimization algorithms have also been proposed to minimize the computational complexity, such as the Genetic Algorithm (GA) [25, 35], Particle Swarm Optimization (PSO) [36], simulating annealing (SA) [37] and so forth. We will compare these algorithms with others new optimization methods in the next sections.

3. Swarm intelligence algorithms

Swarm intelligence algorithms have been widely used in many domains and attracted the attention of researchers working in optimization problems. It is one of the most important research topics in Computational Intelligence Community. The most of swarm intelligence algorithms have been inspired by some intelligent behaviors existing in nature like the collective behavior of a group of social insects (like bees, termites and wasps).

The most respected and popular SI algorithms are particle swarm optimization (PSO), which is inspired by the social behavior of bird flocking or fish schooling, fireworks algorithm (FWA) inspired by the fireworks explosion in the night sky, and ant colony optimization (ACO) which simulates the foraging behavior of ant colony. Nowadays, research efforts on SI are mainly devoted to algorithm design, problem solving, and applications, Hybrid algorithms and variants are actively proposed. The ACO, PSO, and the genetic algorithm (GA) are the most representative swarm intelligence algorithms applied to solve combinatorial optimization problems or used in real-parameter optimization.

3.1 Genetic algorithm (GA)

The genetic algorithm [25, 38], is an optimization algorithm based on techniques derived from genetics and natural evolution: crossovers, mutations, selection, etc. This optimization method has many advantages such as a good convergence, small computing time and high robustness. It can be used to select the optimal phase vector to reduce the PAPR [35], GA decreases the computational load of the PTS technique by searching a small piece of a set of possibilities instead of the whole set as in the classical technique. It searches for the extremum(s) of a function (PAPR function) defined on a space of dimension D , for example $[0 \ 2\pi]$. To use it, we must have some basic elements.

The natural evolution is processed through three main steps as shown in **Figure 3**. First, a population with n chromosomes is generated randomly. Second, this population is exposed to some evolution mechanisms like crossover and mutation to form a new population with the hope of being better. Finally, some parts of the population are selected according to their fitness values (PAPR function) as in natural selection [38, 39]. The algorithm can be stopped when the maximum number of generations ($\max(\text{Gen})$) is reached, or meets a convergence requirement (a targeted PAPR). For more details, the reader can refer to [25].

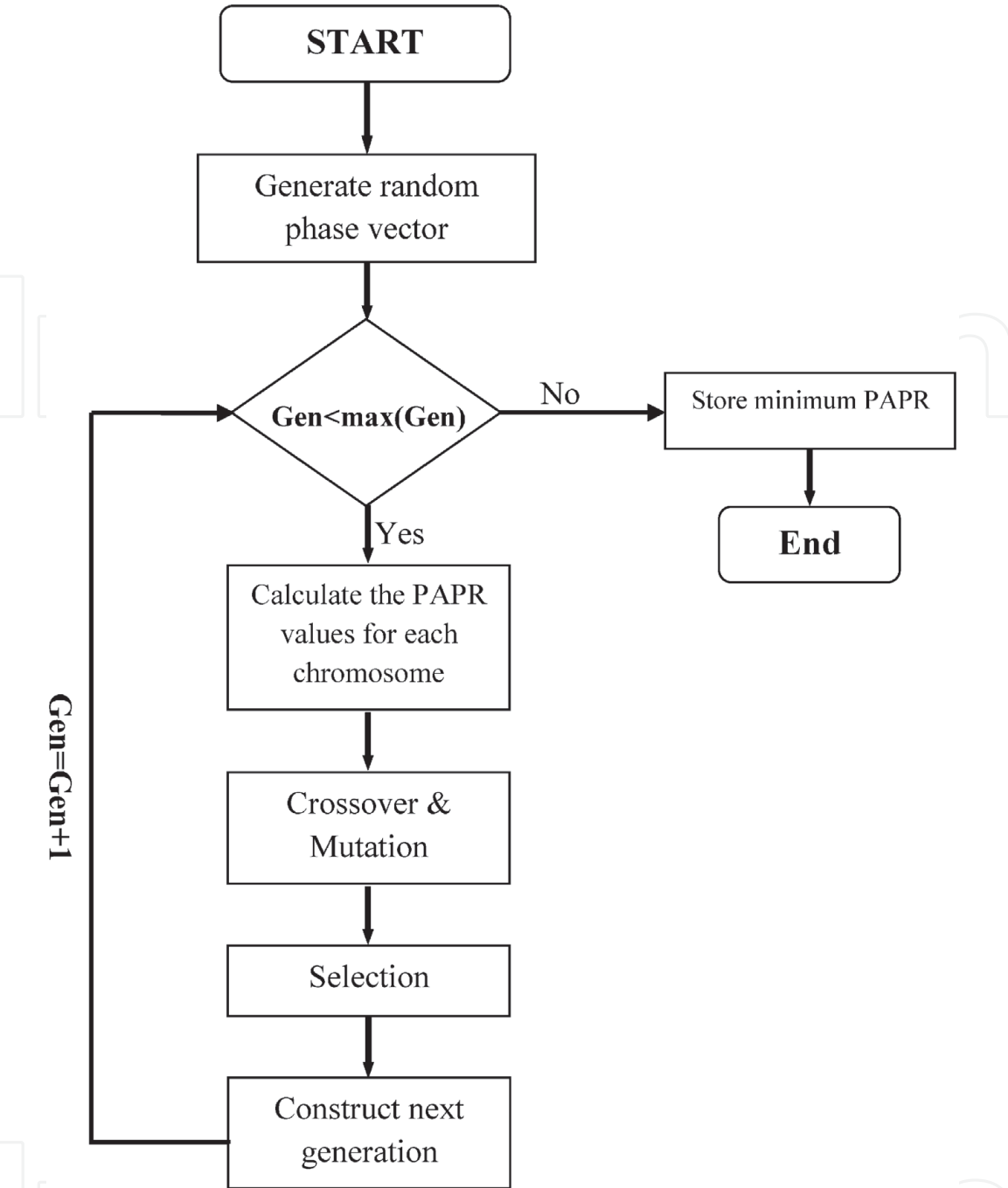


Figure 3.
Flow chart of genetic algorithm.

Parameter	Value
Number of generations (G)	5
Population (P)	5
Crossover rate (CR)	1.0
Mutation rate (MR)	0.05

Table 1.
GA simulation parameters.

The PTS method is combined with a GA to decrease the computational complexity. The basic configuration parameters of the genetic algorithm for the simulations are summarized in **Table 1**. The system uses $N = 64$ subcarriers, with QPSK modulation. The signal is oversampled with the factor $L = 4$ and the weighting

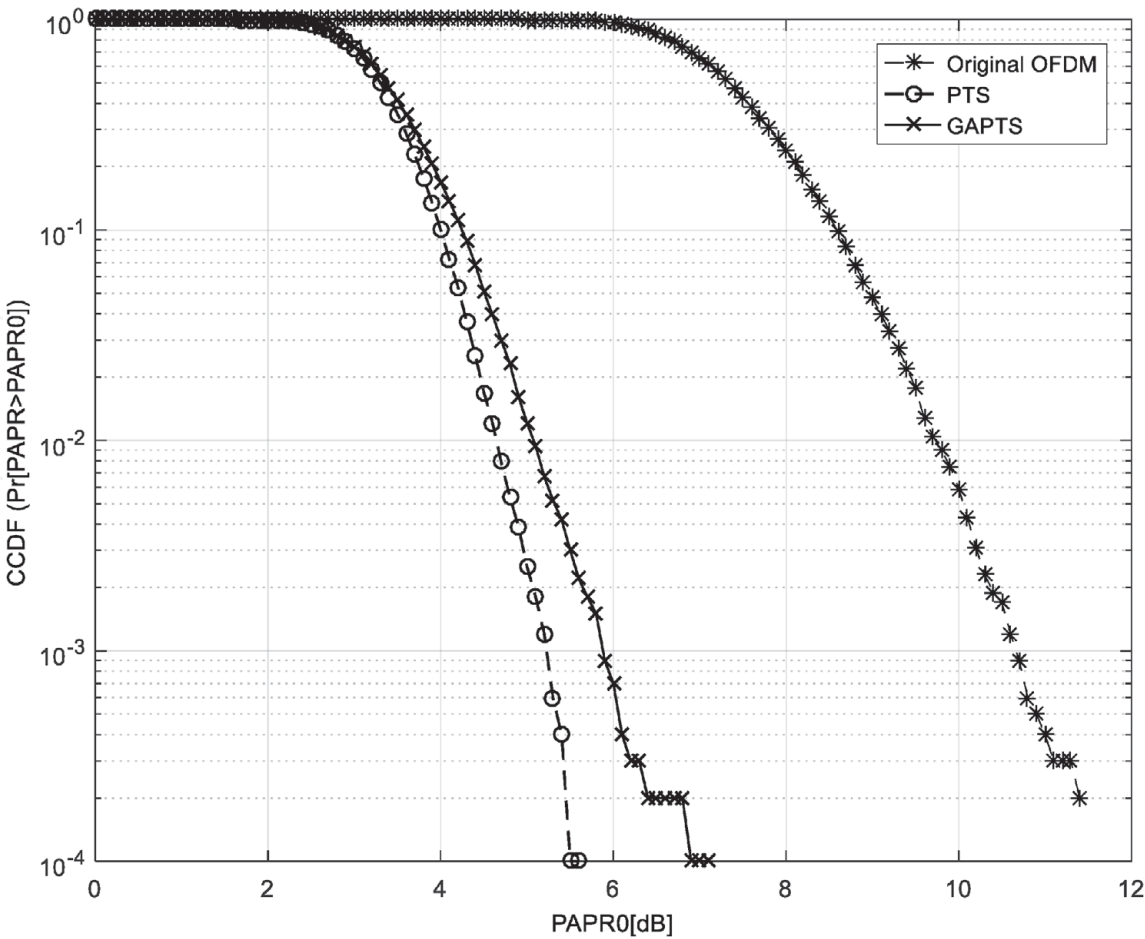


Figure 4.
Comparison of the PAPRo (dB) versus CCDF in OFDM systems for original PTS, and GA-PTS.

system uses a set of phase factors $W = \{1, -1, j, -j\}$ to facilitate signal recovery. For all the results presented in this chapter, 10^4 OFDM symbols are generated, and the simulations are based on the IEEE 802.11/a standard.

Figure 4 shows the CCDF curves of OFDM system without PAPR reduction, the original PTS technique, and the GA-PTS technique. Although the PTS method has better PAPR than the GA-Proposed technique, the computational load of the PTS method is larger than GA-PTS.

3.2 Particle swarm optimization (PSO) based PTS

Particle swarm optimization (PSO) is a population-based global optimization technique put forward originally by Kennedy and Eberhart in 1995 [36, 40–42], it is based on the research of bird and fish flock movement behavior. The PSO algorithm is a computational method used to solve non-linear continuous problems and optimize many practical real life applications such as control reactive power, and Photovoltaic solar systems [43, 44], it has attracted the attention of researchers and a number of versions of PSO have been continuously proposed [45, 46].

In the basic particle swarm optimization algorithm, the population is called swarm and the individuals are called particles, so the PSO works by having a swarm of particles moved in the search space (D-dimensional) according to simple formulae until the optimal solution of the phase problem will be reached. During the movement of the population, each particle is characterized by two parameters: position and velocity. We used the PSO as an optimizer to reduce the PAPR by solving the phase factor problem in (Eq. (5)), the PSO algorithm evaluates each particle with the objective function of PAPR in (Eq. (2)).

During the optimization process; each solution is represented as a particle with a position vector \mathbf{x} , referred to as a moving velocity and a phase weighting factor represented as \mathbf{v} and \mathbf{b} , respectively.

Thus for a K -dimensional optimization, the velocity and position of the i_{th} particle can be represented as $\mathbf{V}_i = (v_{i,1}, v_{i,2}, \dots, v_{i,K})$ and $\mathbf{b}_i = (b_{i,1}, b_{i,2}, \dots, b_{i,K})$ respectively. Basically, each particle has its own best position referred to as \mathbf{pbest} , $\mathbf{b}_i^{Pb} = (b_{i,1}, b_{i,2}, \dots, b_{i,K})$ corresponding to the individual best objective value obtained so far at time t , and the global best (\mathbf{gbest}) particle is denoted by $\mathbf{b}^{Gb} = (b_{g,1}, b_{g,2}, \dots, b_{g,K})$, which represents the best particle found so far at time t in the entire swarm. So the expression of the new velocity $\mathbf{v}_i(t+1)$ for particle i is updated by

$$v_i(t+1) = bv_i(t) + c_1 r_1 (b_i^{Pb}(t) - b_i(t)) + c_2 r_2 (b^G(t) - b_i(t)) \quad (6)$$

where $\mathbf{v}_i(t)$ is the old velocity of the particle i at time t , c_1, c_2 stand for acceleration constants and r_1, r_2 are random numbers between 0 and 1.

Based on the updated velocities (Eq. (6)), new position for particle i is computed according the following equation: $\mathbf{b}_i(t+1) = \mathbf{b}_i(t) + \mathbf{v}_i(t+1)$.

In **Figure 5**, some results of the CCDF of the PAPR are simulated for the OFDM system with the same parameters used, in which the phase weight factor $\mathbf{b} = \{\pm 1, \pm j\}$ is used for PTS and GA-PTS, while the others algorithms like Standard PSO and simulated annealing used a search space $[0 \ 2\pi]$.

As we can see that the CCDF of the PAPR is well improved and the PSO-based PTS technique is capable of attaining a good PAPR performance, it is gradually promoted upon increasing and changing the research space dimension.

3.3 Simulated annealing (SA) based PTS

Simulated Annealing (SA) is an effective and general form of optimization. Over a number of years, the SA algorithm and its many extensions have been extensively

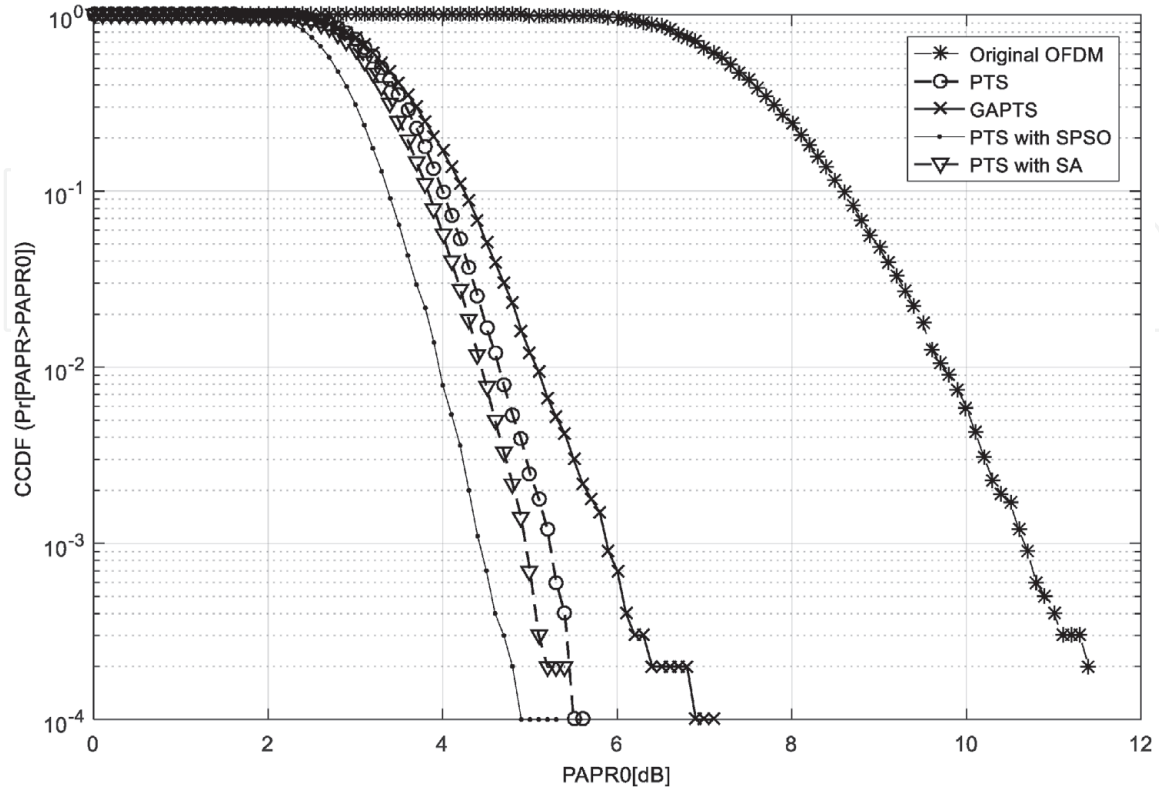


Figure 5. CCDF of the PAPR with the PTS technique searched by SPSO, SA, and GA technique.

employed to solve a wide range of application domains, especially in combinatorial optimization problems [6, 47–49]. It is useful in finding global optima in the presence of large numbers of local optima. This characteristic makes the algorithm generic in the sense that it can be used to solve a variety of optimization problems without the need to change the basic structure of the computations. Over the last few years a number of variations to the original algorithm have been proposed, including parallel versions to speed up the rate of computations [50, 51].

“Annealing” refers to an analogy with thermodynamics, specifically with the way that metals cool and anneal. Simulated annealing uses the objective function of an optimization problem (PAPR in our case) instead of the energy of a material. The Simulated Annealing algorithm is a stochastic optimization method modeled on the behavior of condensed matter at low temperatures.

The Implementation of SA is surprisingly simple, at the outset, the system starts with a high T value, then annealing scheme is applied by slowly decreasing T according to some given procedure. The algorithm is basically hill-climbing except instead of picking the best move, it picks a random move at each T . If the selected move improves the solution (cost function of PAPR), then it is always accepted. Otherwise, in order to accept the states that do not improve the cost function (PAPR function), the algorithm makes the move anyway with some probability less than 1 depending on the PAPR reduction and T . This process randomizes the iterative improvement phase and avoid problems caused by moves that do not improve the solution in an attempt to reduce the probability of falling into a local minimum.

In our study we used SA based PTS algorithm to improve the search of phase factors for PAPR reduction in OFDM signals. QPSK modulation is employed with $N = 64$ subcarriers. The phase weighting factors $W = [0, 2\pi)$ have been used as in SPSO and 10^4 random OFDM symbols have been generated. In **Figure 5** Numerous computer simulations have been conducted to determine that the SA-PTS algorithm can improve PAPR performance better than GA and with a small difference with SPSO. (4,421 dB for SPSO and 4,948 dB for SA at CCDF = 10^{-3}).

3.4 Fireworks algorithm (FWA)

Fireworks algorithm (FWA) is an iterative swarm intelligence algorithm inspired by fireworks explosions in the sky at night, it was proposed by Y. Tan and Y. Zhu in 2010 [21] to searches for optimal solution of some optimization problems. FWA has attracted the attention of researchers and a number of versions of FWA have been continuously proposed [52–55].

The FWA is designed and implemented by simulating the explosion process of fireworks. It's made up of four key components, firstly explosive operator where two explosion processes are employed, explosion strength and explosion amplitude, secondly mutation operation, where the Gaussian mutation is the most widely used, thirdly mapping rule, and the most popular mapping rules are Mirror mapping rule and stochastic mapping rule, lastly as for selection strategy, there are distance-based selection and stochastic selection for keeping diversity of sparks.

3.4.1 Fireworks algorithm based PTS (FWA-PTS)

This section presents the basic principle, implementation and performance of FWA, aiming to develop this algorithm in a systematic and comprehensive way, and easily integrate it into an OFDM system to minimize PAPR. The approach is based on combining the PTS with the FWA to find the optimal phase vectors to reduce the PAPR with the least complexity [56, 57]. The objective function in this case is to minimize the PAPR of transmitted OFDM signals as follows:

$$\begin{cases} \text{Minimize } f_{obj}(\mathbf{b}, \mathbf{x}) = \sum_{v=1}^V \mathbf{b}_v \cdot \mathbf{x}_v \\ \text{Subject to } \mathbf{b}_v = \{e^{j\varphi_v}\}, v = 1, 2, \dots, V \end{cases} \quad (7)$$

where \mathbf{b}_v represent the complex phase factors and the bounds of the potential space is defined by $0 \leq \varphi_v \leq 2\pi$.

Fireworks algorithm starts to run iteratively till the given termination conditions are met. When the FWA algorithm is initiated, a set of Sparks will fill the local space around the Firework, for a good optimization usually we started by five fireworks, and when we search for a point \mathbf{b}_v satisfying $f_{obj}(\mathbf{b}_v) = y$, we can continuously trigger Fireworks in the search space until a Spark checks the target or is close enough to the point \mathbf{b}_v . **Figure 6** is depicting a rough framework of the search optimization algorithm of fireworks to find the best phase vector, the realization of this method consists of four steps as follows:

1. Generate and select N locations for fireworks randomly in the feasible space $[0 \ 2\pi]$.

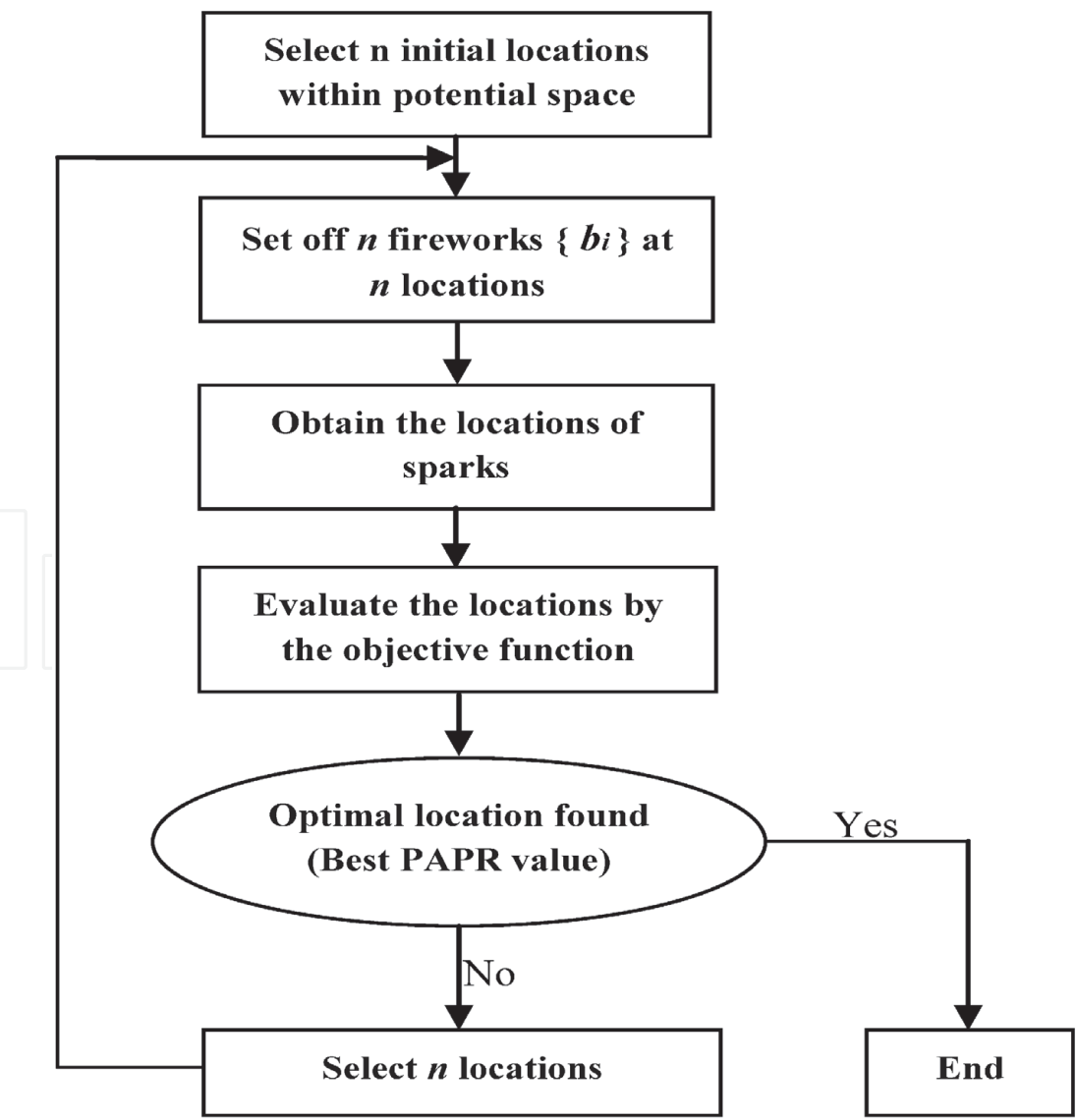


Figure 6.
Flow chart of fireworks algorithm.

2. Evaluate or calculate the fitness value of each firework according to the fitness function ($f_{obj}(\mathbf{b}_v)$). The number of sparks is calculated based on theory formula [21, 57] where the fireworks with better fitness values produce more sparks.
3. The position of sparks is controlled by The explosion amplitude which is determined by the fitness value of that firework [52, 57], each one represents a solution in the feasible space $[0, 2\pi]$. In general, the explosion amplitude for the firework with better fitness value is smaller and vice versa. Gaussian mutation is used to keep the diversity of the population in each iteration.
4. Calculate the best fitness value using objective function. If the terminal condition is met (number of iteration or best PAPR value), stop the algorithm. Otherwise, continue the iteration process. Based on selection strategy the best sparks are selected to form a new population.

In this section, many simulations have been performed based on IEEE 802.11a (Wireless LAN) to verify the performance of PTS-OFDM based on Fireworks algorithm. FWA is used to find the optimal combination of phase factors to reduce PAPR. The OFDM system was simulated with 64 subcarriers, in which 4 sub-blocks are employed, and the PTS, selected mapping (SLM) [58] and GA used $W = 4 \{1, -1, j, -j\}$ phase weighting factors to optimize the PAPR of the modulated OFDM symbol, while others algorithms chose randomly the four phases within the interval $W = [0, 2\pi]$. For the FWA, the parameters were chosen as described in [52], the FWA worked quite well at the setting: $\hat{m} = 5$, $\hat{A} = 40$, $N = 5$, $m = 50$, $a = 0.04$ and $b = 0.8$ [57].

In **Figure 7**, we compare the performance of the FWA-based PTS with the most widely used algorithms for phase optimization such as SPSO, GA, and SA, in terms

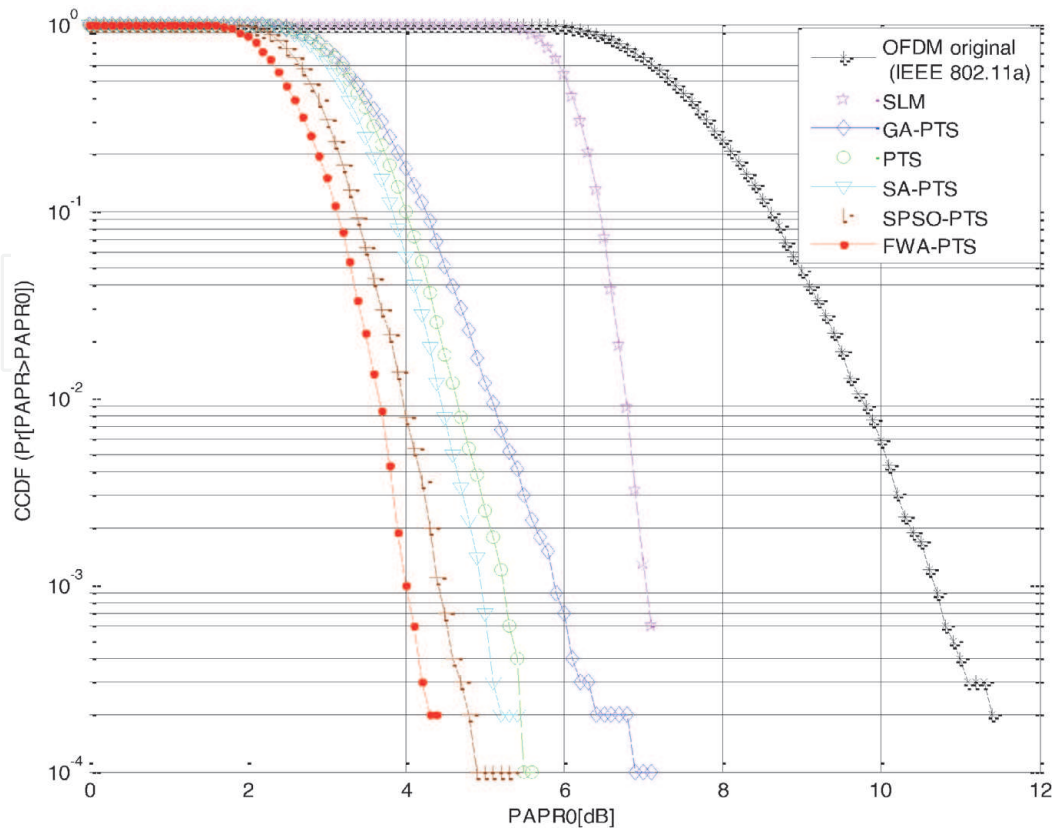


Figure 7.
PAPR reduction with PTS based different searching algorithms.

of CCDF (Complementary Cumulative Density Function). From **Figure 7**, it can be seen that the PTS-FWA scheme performs better than the other algorithms in terms of PAPR reduction. For example, at 10^{-3} of the CCDF, the PAPR is 4 dB, 4.421 dB, 4.948 dB, 5.226 dB, 5.879 dB, 7.034 dB, and 10.66 dB for the FWA, SPSO, SA, PTS, GA-PTS, SLM, and WLAN signals, respectively [57].

3.4.2 Improved versions of the fireworks algorithm

Fireworks Algorithm (FWA) is one of the best swarm intelligence algorithms, recently, many improvement versions of FWA have been proposed and developed based on several modifications. They were proposed to address some inherent limitations of the original algorithm.

Enhanced fireworks algorithm (EFWA) is an improved version of the recently developed Fireworks Algorithm (FWA) based on several modifications, it's proposed to tackle some limitations like the worse quality of the results when being applied on shifted functions or the high computational cost per iteration. In order to that, EFWA proposed five major improvements like a new minimal explosion amplitude check, a new operator for explosion, a new mapping strategy, a new operator for generating Gaussian sparks and for selecting the new population [53].

Dynamic fireworks algorithm (dynFWA) is an adaptive algorithm, it is an improved version of the recently developed EFWA based on an adaptive dynamic local search mechanism. DynFWA uses a dynamic explosion amplitude by increasing or decreasing the amplitude to speed up convergence when the fitness of the best firework could be improved (PAPR in our example) or to narrow the search area when the function could not be improved. In addition, DynFWA proposed the remove of Gaussian mutation operator to improve the computational efficiency [54].

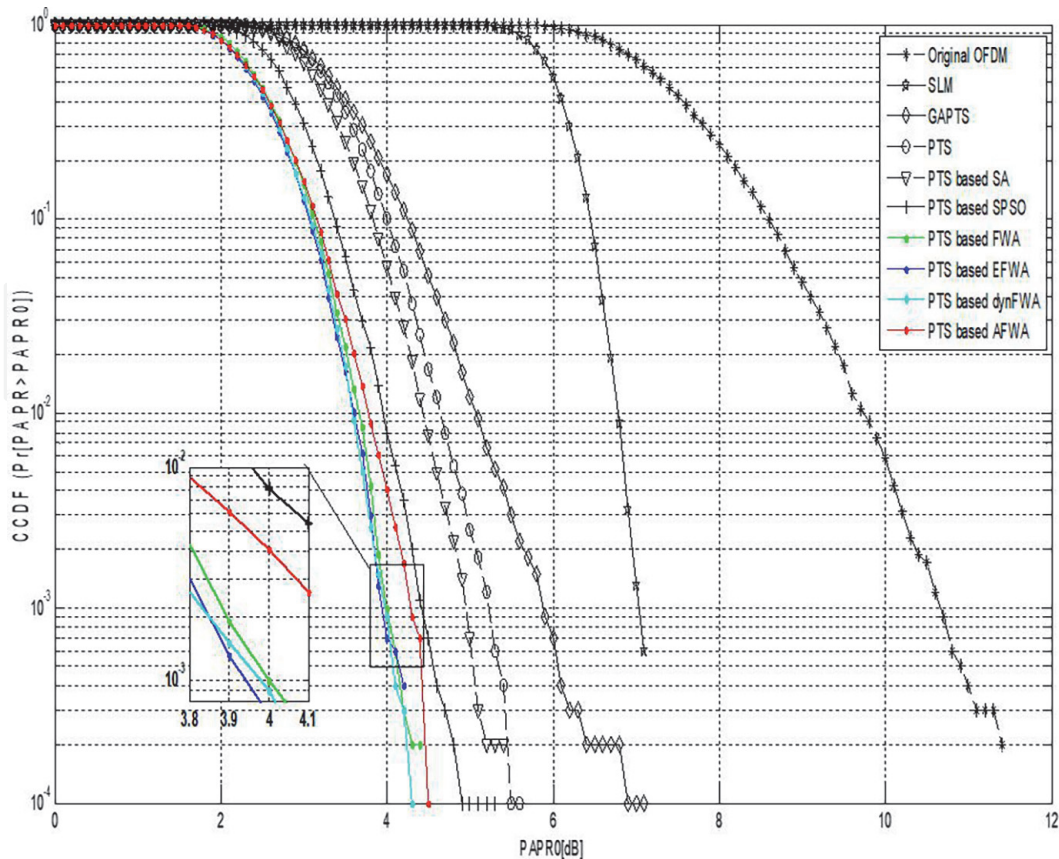


Figure 8.
PAPR reduction performance by the improved versions of the fireworks algorithm FWA.

Another new version called Adaptive fireworks algorithm (AFWA) is proposed to improve FWA and EFWA in term of the explosion amplitude which is a key factor influencing the performance of the algorithm. To improve the mechanism of calculating the amplitude, AFWA used the distance between the best firework and a certain selected individual as the explosion amplitude [55].

Figure 8 shows the simulation results for PAPR reduction of WLAN signals using the Fireworks algorithm based PTS technique and the recently improved versions of FWA (EFWA, DynFWA, and AFWA), compared with the different optimization approaches. From this figure, it is clear that FWA and all developed versions can effectively reduce PAPR in the WLAN-OFDM system. However, their PAPR reduction performance is different, in general, EFWA and dynFWA show a small improvement over the conventional FWA. For $CCDF = 10^{-3}$ we have 3.942 dB and 3.979 dB for EFWA and dynFWA, respectively while AFWA gives 4.283 dB and FWA 4 dB [57].

4. Computational complexity comparison

Beside the optimization accuracy, the convergence speed is an essential parameter for any optimization algorithm. To compare the convergence speed of SI algorithms, we performed some simulations shown in **Figure 9**, which represent the convergence curves of the FWA schemes in comparison with GA and SPSO.

The simulations are performed on a random OFDM symbol with 10 independent generation cycles and 3000 iterations. From these results, we can conclude that the four proposed FWA methods have a much faster convergence speed than SPSO and GA. **Table 2** shows that the fireworks algorithm and its improved versions can find optimal solutions in less than 500 function evaluations.

In terms of computational cost, **Figure 10** shows the time consumed by each algorithm to reduce PAPR. As an experimental platform we used some calculation software, run with a Win 7 operating system on an Intel (R) Core (TM) i5-2430M; 2.4 GHz; and 4 GB of RAM. As we see, the EFWA, dynFWA, and AFWA algorithms

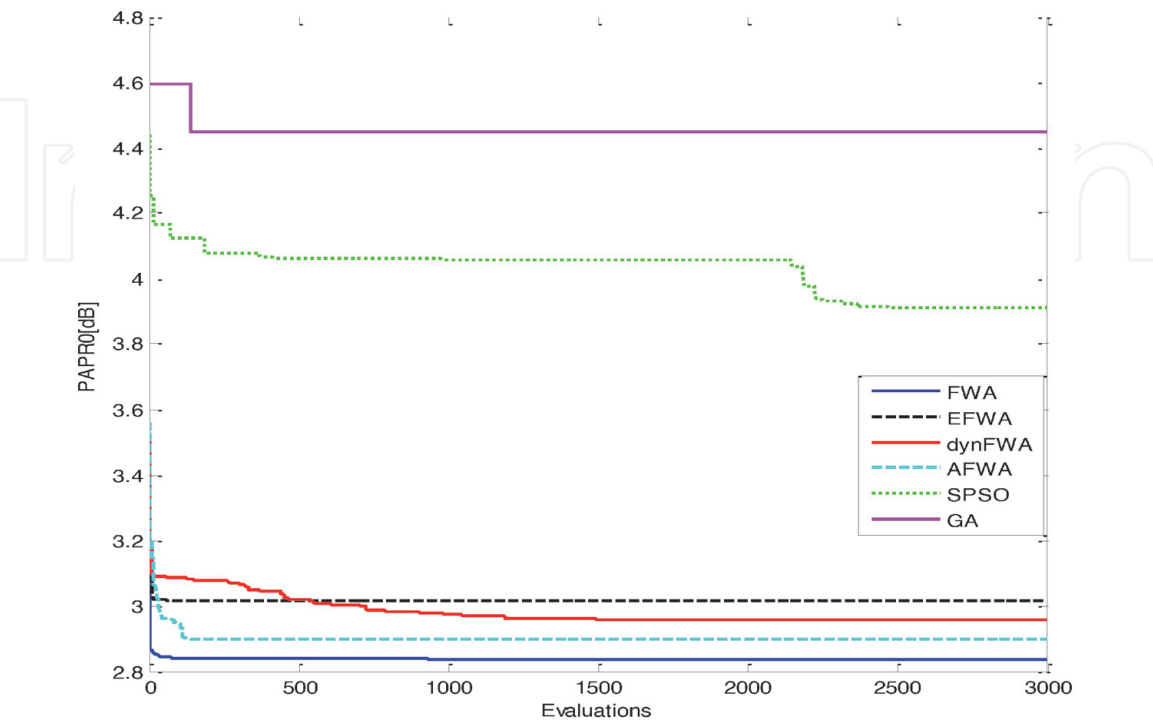


Figure 9.
Convergence curves of the SI algorithms for an OFDM symbol.

Methods	Function evaluations	PAPR [dB]
Original	—	10.66
SPSO	2000	4.055
GA	2000	4.447
FWA	500	2.839
EFWA	500	3.015
DynFWA	500	3.021
AFWA	500	2.9

Table 2.
Performance evaluation by the SI algorithms, on one symbol OFDM over 10 independent runs.

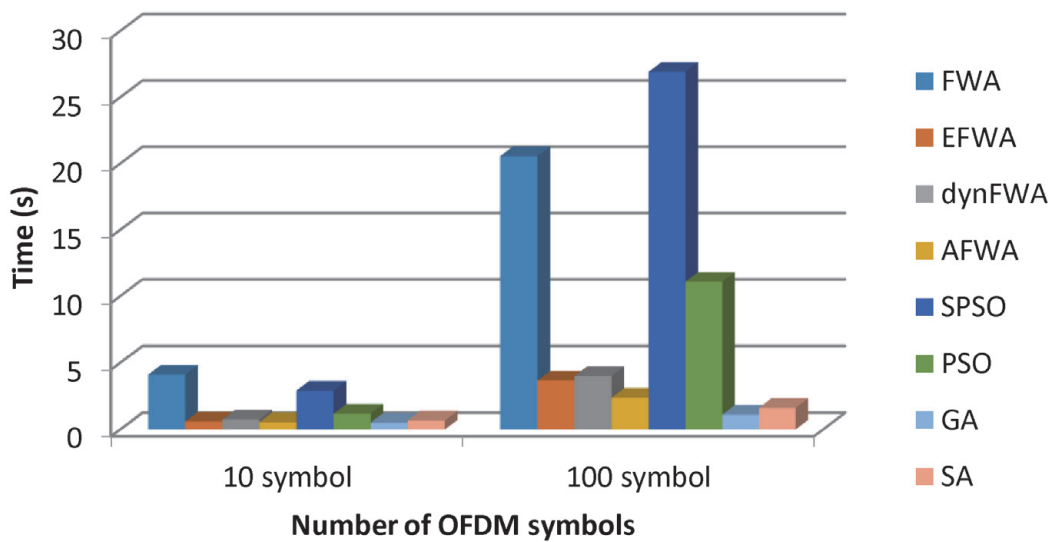


Figure 10.
Time consumed by each algorithm.

are close to each other in execution time, which is much shorter than the FWA and SPSO runtimes.

From these results, we can conclude that EFWA and AFWA have the best computational cost than FWA and dynFWA, while AFWA and dynFWA are very promising compared to other algorithms because of their efficiencies and simplicities.

5. Conclusion

In this chapter, we tried to present the performance of some optimization algorithms based PTS technique to reduce the PAPR of OFDM system with low computational complexity. First of all, OFDM, PAPR problem, and PTS scheme were presented to clarify the problem. Then a concise review on swarm intelligence domain was investigated. In others sections, a brief introduction to GA, PSO, SA and FWA is presented with primary focuses on the basic principal, algorithm study, problem solving, and some applications. Theoretical analysis is also described with completed reference citations of each algorithm. The SI algorithms were compared in terms of CCDF, and simulation results show that, FWA had better performance compared to GA, SA and SPSO. Some improved version of FWA, like EFWA, dynFWA, AFWA were also briefly described, and the comparison show that the

new versions have a promising performance in both optimization accuracy of PAPR and convergence speed over conventional schemes and algorithms.

Conflict of interest

The authors do not have any conflicts of interest to declare.

Appendices and nomenclature

ACO	Ant Colony Optimization
AFWA	Adaptive fireworks algorithm
BER	Bit Error Rate
CCDF	Complementary Cumulative Distribution Function
DynFWA	Dynamic fireworks algorithm
EFWA	Enhanced fireworks algorithm
FWA	Fireworks algorithm
GA	Genetic Algorithm
HPA	High Power Amplifier
IFFT	Inverse Fast Fourier Transform
OFDM	Orthogonal Frequency Division Multiplexing
PAPR	Peak to Average Power Ratio
PSO	Particle Swarm Optimization
SI	Swarm Intelligence
PTS	Partial Transmit Sequence
SLM	Selective Mapping
$x[n]$	Discrete time signal
L	Oversampling factor
X_k	The input complex symbols
$E[.]$	The expected value
V	Number of sub blocks in PTS technique
b^v	Optimized phase vector in PTS technique
W	Phase Weighting Factors
N	Number of subcarriers
v_i	Velocity
f_{obj}	Objective function

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