SETSCI Conference Proceedings 15 , 104-109, 2023

Cognitive Models and Artificial Intelligence Conference

26-28 October 2023, Ankara, Türkiye

https://doi.org/10.36287/setsci.6.1.028

SCA-GWO: A Hybrid Optimization Method Based on the PTS Technique for PAPR Mitigation in OFDM Systems

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Abstract – This work suggests a newly developed partial transmit sequence (PTS) approach consisting of the hybridization of two efficient algorithms, namely, the grey wolf optimization (GWO) algorithm and the sine cosine algorithm (SCA). The SCA-GWO-based PTS technique is investigated to conquer the exponentially increasing computational load of the ordinary PTS technique. The SCA searches for an initial global solution provided to the GWO to increase the wolves' diversity, emphasize exploration, and, thus, avoid less efficient local solutions. The combined SCA-GWO is a balanced optimization variant used in the PTS technique to search for a salient combination of phase factors, which diminishes the peak-to-average power ratio (PAPR) effectively within a very reduced search complexity. The obtained results prove the superiority of the investigated approach in terms of PAPR mitigation and computational load. The SCA-GWO technique minimizes the orthogonal frequency division multiplexing (OFDM) system's PAPR by a rate of 46.07% while representing only 7.32% of the PTS' complexity. A comparison with the state-of-the-art techniques also demonstrates the effective performance of the proposed SCA-GWO in lowering PAPR levels. The SCA-GWO outperforms the whale optimization algorithm (WOA), the genetic algorithm (GA), the harmony search optimization (HSA), and the ant lions optimization (ALO).

Keywords – OFDM, PAPR reduction, PTS, Search complexity, SCA, GWO

I. Introduction

Orthogonal frequency division multiplex (OFDM) is an important multi-carrier communication system that uses multiple orthogonal carriers to transmit data symbols. OFDM is known to be an inherent and robust multicarrier technique when it comes to frequency-selective fading channels. It also offers significant spectral capacity and high bit rate [1]. The OFDM signal is generated after being modulated and passed through an IFFT block. In the time domain, multiple subcarriers are combined, resulting in high peaks in the signal amplitude. This phenomenon is known as peak-to-average power ratio (PAPR), a detrimental aspect that leads to out-of-band radiation, performance degradation, and in-band distortion [2].

To address the PAPR phenomenon, various approaches have been reported in the literature, such as clipping [3], coding [4], peak cancellation and peak windowing [5], non-linear companding [6], DFT spreading [7], tone reservation (TR) [8], tone injection (TI) [9], selective mapping (SLM) [10], and partial transmit sequence (PTS) [11]. Among these approaches, PTS was found to be the best method to reduce PAPR levels without distorting the signal or restricting the number of subcarriers. However, the complexity of the search increases exponentially, making it impractical, especially for a large subblocks' number.

Contemporary literature pays attention to meta-heuristic algorithms to solve time-consuming problems. In [12], fuzzy neural network was employed in the PTS method to mitigate the PTS' complexity. The technique combines the learning and reasoning abilities of the neural network and the fuzzy control scheme, respectively, to properly choose the signal' processing parameters. The results obtained demonstrate the validity of the studied technique as regards search complexity and PAPR reduction.

In [13], Goel and Gupta introduced a new PTS scheme, which addresses the transmitter' side information (SI) free transmission and the exhaustive search' complexity mitigation. The technique is based embedding the side information on the high-power subcarriers' locations using particular segregations. On the other hand, at the receiver side, the SI is extracted using power disparity. This technique provides a reduced bit error rate (BER) degradation and have lesser computations compared to the ordinary PTS scheme.

A hybrid PTS method was presented in [14]. The technique applies the Mu-law expanding and compressing techniques in the PTS scheme. A continuous-unconstrained particle swarm optimization (CUPSO-PTS) method was proposed in [15] to search for a suboptimal combination of phase factors. These are obtained by introducing several continuous-phase PTS methods, and a continuous-unconstrained investigating space is employed to determine the theoretical boundaries. The simulations prove the effectiveness of the method in providing good PAPR levels while saving 84.74% of the ordinary PTS' search complexity.

A related work [16] uses a well-balanced algorithm, called the May Fly Multi objective Algorithm (MOMF) to optimize the phase factors. The technique's performance is tested on the PTS scheme. The investigated technique effectively enhances the performance of the PTS technique compared to other existing optimization methods.

An alternative PTS method was presented in [17]. Based on continuous unconstrained particle swarm optimization

(CUPSO), the latter addresses high peak levels in filter bank multicarrier systems (FBMC). The CUPSO-PTS is considered alongside the input-back-off modulation error rate (IBO-MER) to select the boundaries and improve the convergence rate in the unconstrained continuous investigation area. Furthermore, the MER computations were decreased using CUPSO with IBO signal-to-distortion ratio (IBO-SDR).

A new PTS system, which uses particle swarm optimization (PSO), was presented in [18]. This technique does not require the transmission of side information because it inserts dummy subcarriers into the transmitted data. The idea consists of adding six adaptive sequences of subcarriers to input data, prior to the inverse fast fourier transform (IFFT), and then measure the PAPR after the IFFT block. The proposed algorithm then decides the send of data based on the values of PAPR to a specific threshold.

Another work [19] submitted a PTS scheme that employs firefly algorithm (FF) and a hybrid ant colony optimization (ACO). The provided method noticeably lowers the PAPR. Likewise, Amhaimar et al [20] compared the PTS techniques that are based on swarm intelligence (SI) algorithms. The study was done based on algorithms such, PSO, ACO, fireworks algorithm (FWA), genetic algorithm (GA), and simulated annealing (SA). The performance is assessed based on the accuracy of the solution and the convergence speed.

A new reduced-complexity PTS method is investigated in this study. A combination between the sine cosine algorithm (SCA) [21], and the grey wolf optimization (GWO) [22] algorithm is proposed in the PTS scheme. SCA is a simple and easy-to-implement population-based optimization technique derived from the trigonometric sine and cosine functions. GWO is an optimizer, a meta-heuristic technique that mathematically models the social hierarchy and the hunting mechanism of grey wolves. Despite its effectiveness in solving optimization tasks with fast and accurate properties, it can fall into local optimal solutions due to the lack of population diversity, and thus its performance remains suboptimal. Therefore, SCA is combined with GWO to provide more diversity and improve the quality of solutions.

The rest of the presented study is organized as follows: section 2 introduces OFDM transmitter' basics and defines PAPR, defines the PTS technique and outlines the problem, section 3 provides the suggested model, section 4 presents and discusses the outcomes, and in section 5 the conclusion is given.

II. OFDM SYSTEM, PAPR, AND PTS TECHNIQUE

In an OFDM transmitter, The input block of modulated symbols is presented as

$$X = [X_1, X_2, X_3, \ldots\ldots, X_{N-1}]^T \quad (1)$$

Where T represents the duration of each symbol. The transmitted OFDM signal is calculated as:

$$x_n = \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} \exp\left(\frac{j2\pi kn}{N}\right) \quad (2)$$

The high number of subcarriers include in the OFDM signal causes large peaks in the time domain signal, the PAPR is then defined as the fraction between the average and the peak power. The mathematical expression of the PAPR is given as follows:

$$PAPR = \frac{max\{|x_n|^2\}}{E\{|x_n|^2\}} \quad (3)$$

Where E denotes the expectation operator.

The oversampling factor L is usually selected as $L \geq 4$ to assess a real value of PAPR [23]. The PAPR is estimated using the complementary cumulative distribution function (CCDF). The latter is presented as:

$$CCDF = 1 - (\exp(-PAPR_0))^{NL} \quad (4)$$

Where $PAPR_0$ is a specified threshold.

The principal structure of the PTS technique [11] is presented in Fig. 1. As shown, the N OFDM symbols in each data block X are separated into V equal subblocks.

$$X_v = \left[X_{v,1}, X_{v,2}, \ldots\ldots, X_{v,N-1}\right]^T \quad (5)$$

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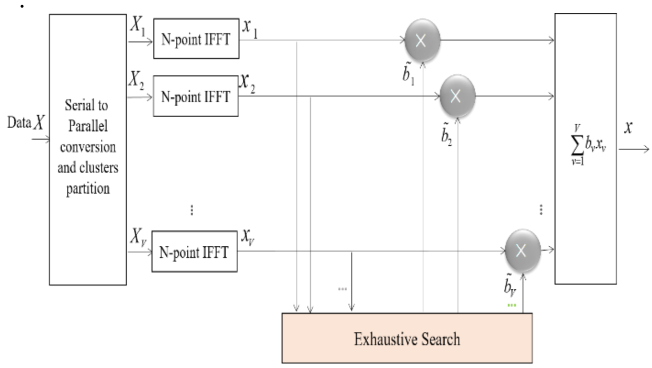

Fig. 1 Block diagram of the conventional PTS technique.

Such that

$$\sum_{v=1}^{V} X_v = X \quad (6)$$

The resulting signal x is acquired after performing an IFFT operation for each sub-block, and then multiplying each resulting time domain signal with a corresponding phase factor. The expression of the resulting signal is then as follows

$$x = IFFT\{\sum_{v=1}^{V} b_v X_v\} = \sum_{v=1}^{V} b_v x_v \quad (7)$$

The optimal phase factors vector is introduced as

$$[\tilde{b}_1, \ldots, \tilde{b}_V] = argmin_b = \{max|\sum_{v=1}^{V} \tilde{b}_V x_v|\} \quad (8)$$

The resulted signal after PAPR minimization is as follows

$$x = \sum_{v=1}^{V} \tilde{b}_V x_v \quad (9)$$

In order to select the optimal phase factors that effectively reduce PAPR levels, an exhaustive search algorithm is used to search for all possible combinations of phase factors. To reduce the complexity of the search, the selection of the phase factors b_v is limited to

$$b_v \epsilon \left\{\exp\left(\frac{j2\pi i}{W}\right)\right\}, \quad i = 0,1, \ldots, W-1 \quad (10)$$

If the first element of the phase factor composite is set to 1, the number of computations performed by the exhaustive search is equal to W^{V-1}, where W is the number of allowed phase factors and V is the number of subblocks. Then, the complexity increases exponentially with the number of sub-blocks. As we know, the PAPR reduction performance of the PTS technique improves with the number of subblocks, which is mainly due to the increase in the number of alternative signals [11]. Clearly, for $W = 4$, and $V = 4$, there are only 43 = 64 candidate signals, whereas, when 8 subblocks are used ($V = 8$), 47 = 16384 alternative signals are there. Therefore, the PTS technique is considered impractical and a reduced complexity PTS technique must be investigated.

III. THE PROPOSED METHODOLOGY

In this work, a hybrid optimization model is proposed for the PTS technique to overcome its exponentially increasing complexity. The hybrid SCA-GWO model is a combination of two efficient optimization algorithms, namely SCA and GWO. This hybridization is mainly carried out to create a powerful and balanced optimization technique in terms of exploration and exploitation. By using SCA, the exploration phase of GWO is strengthened and, therefore, its premature convergence and lack of population diversity will be addressed.

First, we define the objective function (Obj_{fun}) in which the PAPR of the system is evaluated. The main objective is to lower the PAPR levels by searching for the best phase factor compound. Obviously, the best value of the objective function corresponds to the lowest value of PAPR.

$$Obj_{fun}(x) = PAPR(x) \tag{11}$$

SCA is a population-based optimization algorithm proposed by Mirjalili in 2015 \cite{ref23} to handle different optimization tasks. Its concept is based on randomly creating multiple candidate solutions and oscillating them towards or outwards the global solution using sine or cosine functions. The mathematical modeling of the SCA is presented below

$$X^i(t+1) = X^i(t) + r_1 \sin(r_2) \times \left|r_3 X_P^i(t) - X^i(t)\right| \tag{12}$$

$$X^i(t+1) = X^i(t) + r_1 \cos(r_2) \times \left|r_3 X_P^i(t) - X^i(t)\right| \tag{13}$$

Where X^i represents the i^{th} search agent position, X_P represents the target solution, t denotes the current iteration' number. r_1 is used to balance exploration-exploitation by adaptively changing the range of cosine and sine using the below equation $r_1 = a - t\frac{a}{T}$. Where a is constant, t denotes the current iteration, and T represents the maximum iterations' number. r_2 determines the next candidate solution' movement (outwards or towards X_P). r_3 randomly emphasizes or deemphasizes ($r_3 > 1$ or $r_3 < 1$) the effect of the target in designating the distance. The transition between the above equations is done according to r_4; the latter is defined as a random number in [0-1] such as

If r4 < 0.5

$$X^i(t+1) = X^i(t) + r_1 \sin(r_2) \times \left|r_3 X_P^i(t) - X^i(t)\right|$$

Else

$$X^i(t+1) = X^i(t) + r_1 \cos(r_2) \times \left|r_3 X_P^i(t) - X^i(t)\right|$$

GWO is a meta-heuristic algorithm, proposed by Mirjalili et al in 2014 \cite{ref24} to solve continuous optimization problems with fast and accurate convergence properties. Mainly inspired from the unique hunting behavior of grey wolves, the mathematical modeling of encircling the prey behavior of the grey wolves is as follows

$$D = |C.X^{best} - X(t)| \tag{13}$$

$$X(t+1) = X^{best} - AD \tag{14}$$

Where X^{best} is the target prey' position, X is the current wolf position, t denotes the current number of iteration, '.' represents elementwise multiplication. A and C are denoted as coefficient vectors, defined as: $A = 2ar_1 - a$, and $C = 2r_2$. Where a is referred to as a linearly reduced function ($a = [2, 0]$), and r_1 and r_2 represent random numbers in the interval $[0, 1]$. In order to mathematically simulate the wolves hunting technique, the top three members of the wolves' hierarchy are saved and presented as the three best solutions found during the iterations, and the rest of the wolves population (including the omega wolves) are forced to update their location in accordance with the location of the top three wolves. In this regard, the following equations are presented.

$$\begin{aligned} D^{\alpha} &= |C_1.X^{\alpha} - X| \\ D^{\beta} &= |C_2.X^{\beta} - X| \\ D^{\delta} &= |C_3.X^{\delta} - X| \end{aligned} \tag{15}$$

$$\begin{aligned} X^1 &= X^{\alpha} - A^1.D^{\alpha} \\ X^2 &= X^{\beta} - A^2.D^{\beta} \\ X^3 &= X^{\delta} - A^3.D^{\delta} \end{aligned} \tag{16}$$

$$X(t+1) = \frac{X^1 + X^2 + X^3}{3} \tag{17}$$

The transition between exploration and exploitation is guided by the absolute random value of 'A'. If $|A| \geq 1$ then the grey wolves head for the exploration of new regions in the search area.

Whereas, if $|A| < 1$, then the grey wolves head for the exploitation and thus they converge towards prey' position.

The process of the proposed technique starts with the extraction of an initial solution from the SCA algorithm. The latter is then injected into the GWO to initialize the investigation from a promising area, thus improving the overall search. Then, depending on the value of 'A', the grey wolves switch from exploration to exploitation. At the end, if the imposed stopping criterion is verified, the algorithm outputs the best solution found so far (best phase factors compound).

The pseudo-code of the proposed SCA-GWO is presented below:

1. **Initialize** the SCA population (P_1) with random candidate solutions.
2. **Calculate** the objective function at each candidate solution position (Obj_{fun} (X^i)) to find the best phase factors composite (X_P).
3. **While** $t \leq I_1$ (I_1 denotes the maximum number of iterations of the SCA)
4. **Update** r_1
5. **For** each candidate solution **do**
6. **Update** r_2, r_3, r_4
7. **Update** the candidate solutions' positions using Eq. (12)

8. **End for**
9. $t = t+1$
10. **End while**
11. **Return** the global best solution (X_P)
12. **Initialize** the grey wolves population (P_2) with random grey wolves positions with consideration to the initial solution (X_P)
13. **While** $t \le I_2$ do (I_2 denotes the maximum number of iterations of the GWO*)*
14. **For** each grey wolf **do**
15. **Evaluate** the objective function
16. **Update** alpha, beta, and delta positions (X^{α}, X^{β}, X^{δ})
17. **Update** a, A, and C
18. **Update** each grey wolf position according to Eq. (17)
19. **End for**
20. $t = t+1$
21. **End while**
22. Output the best solution found so far, i.e. the best phase factors compound which yields the minimum of PAPR value.

As it is illustrated in the above pseudo-code, the algorithm is composed of two main loops that are repeated I1 and I2 times for a population of P_1 and P_2 respectively (from line 3 to line 10 for the former loop and from line 13 to line 21 for the latter loop). Therefore, the search complexity of the proposed technique is equal to $(I_1 \times P_1) + (I_2 \times P_2)$ Compared to this, the conventional PTS technique requires W^{V-1} searches to output optimal phase factors composite.

IV. Simulation Results And Discussions

In order to evaluate the performance of the SCA-GWO based PTS technique, MATALB simulations were performed. We have generated 10000 random OFDM frames. The 16 QAM modulation is used and different numbers of subcarriers are employed in the simulation. The phase factors are chosen from a set of $\{\pm 1, \pm j\}$ $(W=4)$. We chose an oversampling factor of 4 to verifiably estimate the PAPR. The SCA-GWO is compared with conventional OFDM, ordinary PTS, and other optimization-based PTS techniques such as GA-PTS, GWO-PTS, HSA-PTS, SCA-PTS, WOA-PTS, and ALO-PTS. For a fair comparison, the parameters of the compared algorithms are set as they are mentioned in their original papers. The simulation parameters are summarized in Table 1.

Table 1. Simulation parameters

Parameters	Values
Type of modulation	16-QAM
Number of subcarriers (N)	64,128,256
Oversampling factor (L)	4
Number of phase factors (W)	4
Number of subblocks (V)	2,4,8,16
Number of iterations (I_1, I_2)	20,20
Number of population (P_1, P_2)	30,30

In order to correctly choose the iterations and population numbers of SCA and GWO, a convergence analysis is first performed. An OFDM frame was repeated 100 times to obtain the average of the best objective function values. The convergence performance of SCA and GWO are shown in Fig. 2 and Fig. 3, respectively. Referring to the two convergence analyses, the average of the best values of the objective function after 20 iterations remained almost the same, as it is 0.21 dB for both analyses. Therefore, $I_1 = I_2 = 20$ is the appropriate selection for the number of iterations.

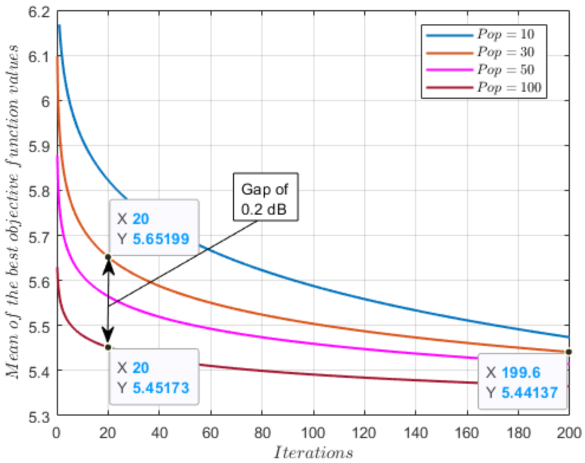

Fig. 2 Convergence curves of the SCA using different numbers of population.

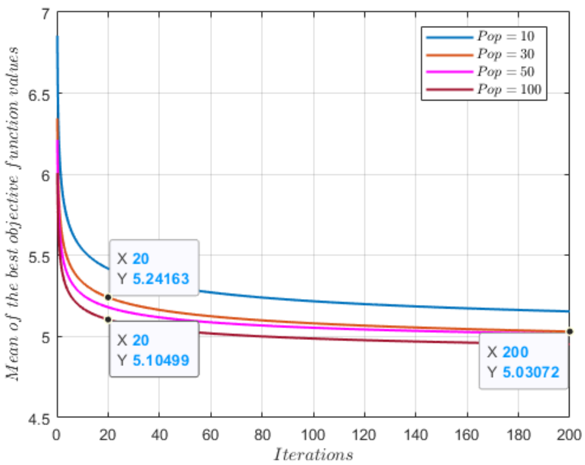

Fig. 3 Convergence curves of the GWO using different numbers of population.

As shown in Fig. 2, at 20 iterations, the average PAPR using a population of 10 ($P_1 = 10$) is degraded by a value of 0.37 dB compared to that obtained with $P_1 = 100$. On the other hand, the convergence curve ($P_1 = 30$) is degraded by only 0.2 dB compared to that of P_1=100, which is considered negligible. Therefore, the SCA is employed using $I_1 = 20$ and $P_1 = 30$.

Analyzing Fig. 3, it is obvious that convergence can be justified using a population of 30 wolves ($P_2 = 30$) since it is only degraded within 0.14 dB compared to that using 100 wolves ($P_2 = 100$). The population of 10 wolves is not considered appropriate because the difference with 100 wolves is considerable (0.31 dB). Therefore, $P_2 = 30$ and $I_2 = 20$ are the appropriate parameters for the SC-GW simulation. The complexity of the SC1-GWO is then $(I_1 \times P_1) + (I_2 \times P_2) = (20 \times 30) + (20 \times 30) = 1200$.

In Fig. 4, the PAPR reduction performance of the SCA-GWO using V=8 is compared with the conventional OFDM technique and the ordinary PTS technique. The CCDF curves of GWO-PTS and SCA-PTS are also performed to compare their performance with the proposed hybrid model. Analyzing the Fig, the proposed technique effectively reduces the PAPR of the conventional OFDM technique by 46.07% and outperforms the SCA-PTS

and GWO-PTS techniques by 0.5 dB and 0.31 dB, respectively. The difference between the CCDF curves of the ordinary PTS technique and that of the SCA-GWO-based PTS scheme is minimal and considered negligible (0.08 dB difference). Furthermore, the complexity of the proposed technique is only 1200/47=1200/16384=7.32% of that by the PTS scheme.

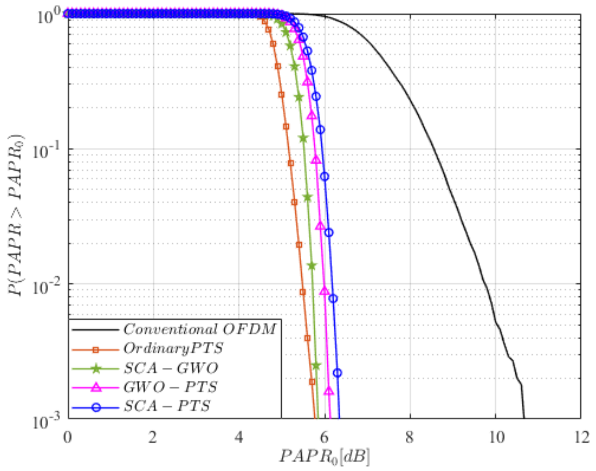

Fig. 4 CCDF curves of PAPR reduction using *V*=8.

In order to demonstrate the improved performance of the technique, larger sub-blocks are used (*V*=16). As shown in Fig. 5, the CCDF curve of the ordinary PTS technique is neglected, mainly due to the massive number of computations required by the method to reach the optimal solution; for $V=16$, $W^{V-1}=4^{15}=1.07\times10^9$ calculations are required. The superior performance of SCA-GWO compared to other methods is evident. SCA-GWO outperforms GA-PTS, HSA-PTS, ALO-PTS, and WOA-PTS by 0.17 dB, 0.55 dB, 0.8 dB, and 0.4 dB, respectively, using the same search complexity. Thus, the PAPR reduction performance can be classified as SCA-GWO>GA>WOA>HSA>ALO.

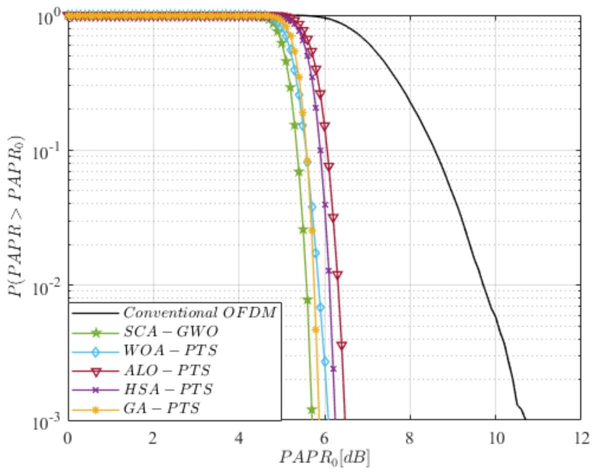

Fig. 5 CCDF curves of PAPR reduction using *V*=16.

Table. 2 shows and compares the performance of the proposed SCA-GWO using different numbers of subcarriers with other effective techniques. The SCA-GWO is found to be effective in reducing PAPR as the number of subcarriers increases compared to WOA-PTS, HSA-PTS, GA-PTS, and ALO-PTS.

Table 2. PAPR performance comparisons using *V*=16.

Method	Complexity	PAPR (dB)		
		N=64	*N*=128	*N*=256
OFDM	--	10.7	11.1	11.3
WOA-PTS	$I\times P$=40×30=1200	6.1	6.8	7.3
HSA-PTS	$I\times P$=40×30=1200	6.25	6.9	7.45
GA-PTS	$I\times P$=40×30=1200	5.87	6.53	7.31
ALO-PTS	$I\times P$=40×30=1200	6.5	7.1	7.7
SCA-GWO	$(I_1\times P_1)+(I_2\times P_2)$= 1200	5.7	6.38	7.15

V. CONCLUSION

In this work, a new PTS technique based on the combination of two efficient algorithms, namely SCA and GWO, is proposed. The SCA-GWO based PTS model is investigated to cope with the exponential increase in the complexity of the ordinary PTS technique. The proposed scheme achieved approximately the same exhaustive search's performance (0.08 dB difference) while representing only 7.3% of its complexity. The simulation results prove the superiority of the proposed scheme over GA-PTS, HSA-PTS, ALO-PTS and WOA-PTS. The applicability of the method using larger subblock partitions (*V*=16) and different numbers of sub-carriers (*N*=64, 128, 256) is verified. The proposed method, hence, can be an alternative solution for PAPR reduction in OFDM systems.

ACKNOWLEDGMENT

This work was supported by the Directorate- General for Scientific Research and Technological Development (DG-RSDT) of Algeria under PRFU project number A25N01UN240120220001.

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