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Performance Analysis of BFO for PAPR Reduction in OFDM

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Abstract*— Partial transmit sequence (PTS) is one of the attractive techniques to reduce the peak-to-average power ratio (PAPR) in orthogonal frequency division multiplexing (OFDM) system. As conventional PTS technique requires an exhaustive searching over all the combinations of the given phase factors, which results in the computational complexity increases exponentially with the number of the sub-blocks. In this paper, we aim to obtain the desirable PAPR reduction with the low computational complexity. Since the process of searching the optimal phase factors can be categorized as combinatorial optimization with some variables and constraints, we propose a novel scheme, which is based on a bacteria foraging optimization, to search the optimal combination of phase factors with low complexity. To validate the analytical results, extensive simulations have been conducted, showing that the proposed schemes can achieve significant reduction in computational complexity while keeping good PAPR reduction.

Index Terms*— Bacteria foraging optimization (BFO), orthogonal frequency division multiplexing (OFDM), partial transmit sequences (PTS), peak-to-average power ratio (PAPR).

I. INTRODUCTION

The limitation of modulation schemes in existing communication systems has become an obstruction in further increasing the data rate. Hence, next generation mobile communication systems need more sophisticated modulation scheme and information transmission structure. Orthogonal frequency division multiplexing (OFDM) has therefore been adopted due to its superior performance. OFDM is a widely used communication technique in broadband access applications requiring high data rates.

In an OFDM system, the output is the superposition of multiple sub-carriers. In this case, some instantaneous power outputs might increase greatly and become far higher than the mean power of the system when the phases of these carriers are same. This is also defined as large Peak-to-Average Power Ratio (PAPR). High PAPR is one of the most serious problems in OFDM system. To transmit signals with high PAPR, it requires power amplifiers with very high power scope. These kinds of amplifiers are very expensive and have low efficiency-cost. If the peak power is too high, it could be out of the scope of the linear power amplifier. This gives rise to non-linear distortion which changes the superposition of the signal spectrum resulting in performance degradation. If there are no measures to reduce the high PAPR, OFDM system could face serious restriction for practical applications [1]–[3].

To combat high PAPR, one intuitive solution is to adopt amplifiers to have larger trade-off range. However, these types of amplifiers are generally expensive and have low efficiency-cost, and therefore are of no practical use. On the other side, certain algorithms were introduced and been proved to have a good performance of high PAPR reduction. Recently, various solutions have been proposed to alleviate the high PAPR problem, such as selective mapping (SLM) [5], [6], partial transmit sequence (PTS) [7], [8], [9], companding transform [10], [11], and active constellation extension (ACE) [12], [13]. One of the best techniques to reduce PAPR is partial transmit sequence (PTS) in OFDM. Hence, in this paper, an optimization technique with the existing PTS method is proposed. With all this the need for optimizing the solution is a must to ensure a better solution and hence better performance [4].

The principle of PTS is to divide the input data block into several disjoint sub-blocks and transform these sub-blocks into partial transmit sequences by inverse fast Fourier transform (IFFT). Then, the transmitted sequence with minimum PAPR is selected from a set of candidate sequences formed by multiplying partial transmit sequences with a set of phase factors. Using the PTS technique needs an exhaustive search of the possible phase factors to obtain optimal PAPR performance. Moreover, the computational load becomes impractical while the number of sub-blocks or phase factors increased. Although much research has been devoted to improve the PAPR performance in OFDM systems, much research has been done on reducing the computational load of PTS technique [14]–[16].

However, the big issue of finding the optimal phase combination for PTS sequence is complex and difficult when the number of subcarriers and the order of modulation are increased. To reduce the computational complexity, many extensions of PTS schemes have been proposed recently [7]–[12], such as adaptive PTS approach [13]. However, for all these searching methods, either the PAPR reduction is suboptimal or the complexity is still high. In this paper, we propose a novel solution to reduce the complexity while keeping the optimal combination of the phase factors to reduce the PAPR largely. Specifically, we apply the Bacteria foraging optimization (BFO) [28] to search the optimal combination of phase factors with largely reduced complexity. Numerical results show that the proposed scheme can achieve better PAPR reduction with lower computational complexity compared to that of the former approaches.

The rest of this paper is organized as follows. In Section II, a typical OFDM system is given and the PAPR problem is formulated and then PTS is explained. Then, BFO is proposed to search the optimal combination of phase factors for PTS in Section III. In Section IV, the performance of OFDM signals are studied and evaluated using the proposed scheme to reduce the PAPR through computer simulations, followed by conclusions in Section V.

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II. OFDM SYSTEM WITH PTS TO REDUCE PAPR

OFDM is one of the many multicarrier modulation techniques, which provides high spectral efficiency, low implementation complexity, less vulnerability to echoes and non linear distortion. Due to these advantages of the OFDM system, it is vastly used in various communication systems. But the major problem one faces while implementing this system is the high peak to average power ratio of this system. A large PAPR increases the complexity of the analog to digital and digital to analog converter and reduces the efficiency of the radio frequency (RF) power amplifier [16]. Regulatory and application constraints can be implemented to reduce the peak transmitted power which in turn reduces the range of multi carrier transmission.

However, the recent interest in the applications of OFDM to wireless networks has resulted in development of methods to combat PAPR problem. PAPR reduction techniques are therefore of great importance for OFDM systems [17]. Coherent addition of N signals of same phase produces a peak which is N times the average signal.

A. PAPR of a multicarrier signal

Let the data block of length N is represented by a vector. Duration of any symbol in the set X(k) is T and represents one of the sub carriers set. As the N sub carriers chosen to transmit the signal are orthogonal to each other, so we can have where and NT is the duration of the OFDM data block X(K). The complex data block for the OFDM signal to be transmitted is given by the IFFT relation which is

$$x(t) = \sum_{K=1}^{N-1} X(k) e^{j2\pi k f_0} \quad (1)$$

$$X(X(0), X(1),.....X(N-1))$$

Let be the input block of N symbols, f_0 is the Bandwidth of each sub carrier. Then the Peak to average power ratio (PAPR) is expressed as

$$PAPR = \max\,(0 \le t \le T_s)\,\frac{|x(t)|^2}{E[|x(t)|^2]} \quad (2)$$

Where $|x(t)|^2$ represents peak output power, $E[|x(t)|^2]$ means average output power. E denotes the expected value, x(t) represents the transmitted OFDM signals which are obtained by taking IFFT operation on modulated input symbols (k).

For an OFDM system with N sub-carriers, the peak power of received signals is N times the average power when phase values are the same. The PAPR of baseband signal will reach its theoretical maximum at $PAPR\ (dB)$ =10log N [4].

PAPR is stochastically measured in terms of CCDF (complementary cumulative distribution function) which is given as

$$CCDF\,(PAPR_0) = Pr\,(PAPR > PAPR_0) \quad (3)$$

CCDF of PAPR denotes the probability that the PAPR of the data exceeds of a given threshold value $PAPR_0$.Using the central limit theorem on OFDM signals, when the time domain signals follow the Gaussian distribution with zero mean, the amplitude of multi carrier signal has a Rayleigh distribution and is given by

$$F\,(PAPR_0) = 1 - \exp\,(PAPR_0) \quad (4)$$

B. Principle of Operation

Fig.1 illustrates the block diagram of PTS scheme. In PTS technique the data information in frequency domain X_i is separated into M non-overlapping sub-blocks and each sub-block vectors has the same size N.

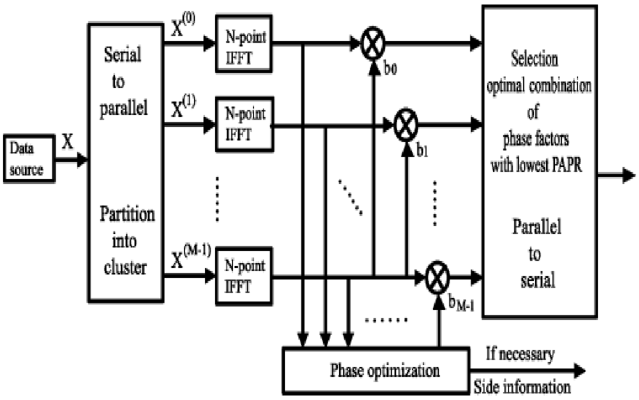

Fig.1 Block diagram of PTS algorithm [3]

Hence, for every sub-block, it contains N/M nonzero elements and set the rest part to zero. Assume that these sub-blocks have the same size and no gap between each other, the sub-block vector is given by

$$\hat{X} = \sum_{i=1}^{M} b_i X_i \quad (5)$$

where $b_i = e^{j\varphi_i}$ $\varphi_i \in 0,2\pi$ *and* $i = 1,2......,M$ is a weighting factor been used for phase rotation . where b_i are the phase factors expressed as

$$b_i = e^{\frac{j2\pi w}{W}}, w = 0,1............W-1 \quad (6)$$

and W is the allowed number of phase angles The signal in time domain is obtained by applying IFFT operation on Xi, that is

$$\hat{x} = IFFT(\hat{X}) = \sum_{i=1}^{M} b_i\, IFFT(X_i) = \sum_{i=1}^{M} b_i \,.\, x_i \quad (7)$$

Select one suitable factor combination b = $[b_{1,2},\ldots,b_i]$ which makes the result achieve optimum. The combination can be given by

$$b = [b_1, b_2,........bi] = \arg\min_{(b_1,b_2......b_i)} (\max_{1\le n\le N} |\sum_{i=1}^{M} b_i . x_i|^2) \quad (8)$$

Where argmin $(\cdot)$ is the judgment condition that output the minimum value of function. In this approach the best b is found so as to optimize the PAPR performance. The additional cost that have to pay is the extra V-1 times IFFTs operation [3]. In conventional PTS approach, it requires the PAPR value to be calculated at each step of the optimization algorithm, which will introduce tremendous trials to achieve the optimum value [17], [18]. Furthermore, in order to enable the receiver to identify different phases, phase factor b is required to send to the receiver as sideband information (usually the first sub-block b_1, is set to 1). So the redundancy bits account for $(M-1)\log_2 W$, in which M represents the number of sub-block, W indicates possible variations of the phase. This causes a huge burden for OFDM system, so studying on how to reduce the computational complexity of PTS has drawn more attentions, nowadays.

III. PROPOSED PAPR REDUCTION APPROACH

To tackle complex search problems of the real world, scientists have been drawing inspiration from nature and natural creatures for years. Optimization is at the heart of many natural processes like Darwinian evolution, group behavior of social insects, and the foraging strategy of other microbial creatures. Natural selection tends to eliminate species with poor foraging strategies and favor the propagation of genes of species with successful foraging behavior since they are more likely to enjoy reproductive success. Since a foraging organism or animal takes necessary action to maximize the energy intake per unit time spent for foraging, considering all the constraints presented by its own physiology such as sensing and cognitive capabilities, environment (e.g., density of prey, risks from predators, physical characteristics of the search space), the natural foraging strategy can lead to optimization and essentially this idea can be applied to solve real-world optimization problems [28]. Based on this concept, Passino proposed an optimization technique known as the bacterial foraging optimization algorithm (BFOA). To date, BFOA has successfully been applied to real-world problems such as optimal controller design [31], harmonic estimation [34], transmission loss reduction, active power filter synthesis, and learning of artificial neural networks [37]. One major step in BFOA is the simulated chemotactic movement. Chemotaxis is a foraging strategy that implements a type of local optimization, where the bacteria try to climb up the nutrient concentration to avoid noxious substance and search for ways out of neutral media.

Recently BFO algorithm has been successfully applied in different applications and shown that it is giving better performance compared to different constrained PSO and GA. Due to multimodal, nonlinear, and high-dimensional nature of the parameter space, the problem seems to be a good application area for BFO. BFO has a better chance to attain the global optimum and BFO is less sensitive to initialization, however, a good initial guess speeds up the computation. All these features make BFO more attractive for direction finding applications [33], [35].

A. The Bacteria Foraging Optimization Algorithm

During foraging of the real bacteria, locomotion is achieved by a set of tensile flagella. Flagella help an E.coli bacterium to tumble or swim, which are two basic operations performed by a bacterium at the time of foraging [28]. When they rotate the flagella in the clockwise direction, each flagellum pulls on the cell. That results in the moving of flagella independently and finally the bacterium tumbles with lesser number of tumbling whereas in a harmful place it tumbles frequently to find a nutrient gradient. Moving the flagella in the counterclockwise direction helps the bacterium to swim at a very fast rate. In BFO algorithm the bacteria undergoes chemotaxis, where they like to move towards a nutrient gradient and avoid noxious environment. Generally the bacteria move for a longer distance in a friendly environment. Fig.2 depicts how clockwise and counter clockwise movement of a bacterium take place in a nutrient solution.

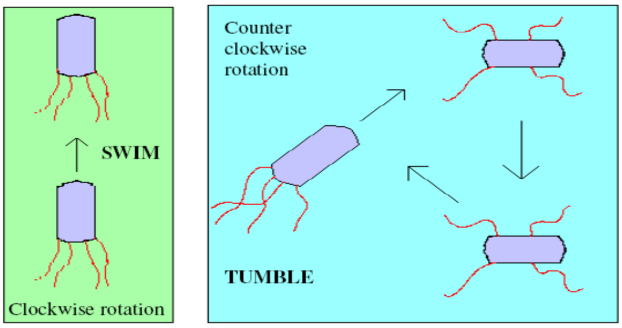

Fig.2 Swim and tumble of a bacterium [28]

When they get food in sufficient, they are increased in length and in presence of suitable temperature they break in the middle to from an exact replica of itself. This phenomenon inspired Passino to introduce an event of reproduction in BFOA [30]. Due to the occurrence of sudden environmental changes or attack, the chemotactic progress may be destroyed and a group of bacteria may move to some other places or some other may be introduced in the swarm of concern. This constitutes the event of elimination-dispersal in the real bacterial population, where all the bacteria in a region are killed or a group is dispersed into a new part of the environment.

The information processing strategy of the algorithm is to allow cells to stochastically and collectively swarm toward optima. This is achieved through a series of three processes on a population of simulated cells:

1) 'Chemotaxis' where the cost of cells is derated by the proximity to other cells and cells move along the manipulated cost surface one at a time (the majority of the work of the algorithm),
2) 'Reproduction' where only those cells that performed well over their lifetime may contribute to the next generation, and
3) 'Elimination-dispersal' where cells are discarded and new random samples is inserted with a low probability.

B. Flowchart of BFOA Algorithm

The different steps used in BFOA are shown in Fig.3.

C. Formulation of BFO Algorithm in PTS

As stated in above section, Bacteria perceive the direction to food based on the gradients of chemicals in their environment. Similarly, bacteria secrete attracting and repelling chemicals into the environment and can perceive each other in a similar way. Using locomotion mechanisms (such as flagella) bacteria can move around in their environment, sometimes moving chaotically (tumbling and spinning), and other times moving in a directed manner that may be referred to as swimming. Bacterial cells are treated like agents in an environment, using their perception of food and other cells as motivation to move, and stochastic tumbling and swimming like movement to re-locate. Depending on the cell-cell interactions, cells may swarm a food source, and/or may aggressively repel or ignore each other.

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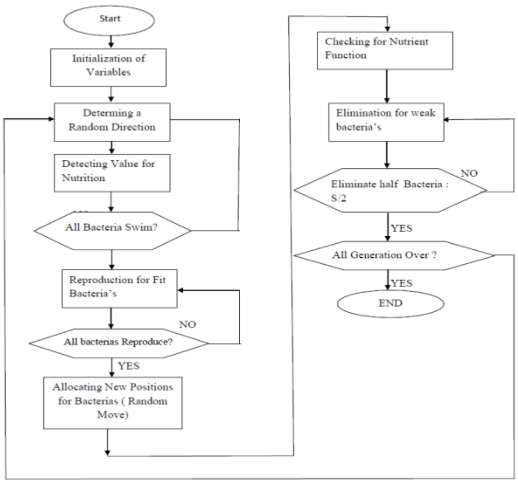

Fig.3 Flowchart of BFO

Now suppose that the ultimate goal is to find the minimum of J(q). To solve this non-gradient optimization problem, BFOA mimics the four principal mechanisms observed in a real bacterial system:

- chemotaxis,
- swarming,
- reproduction, and
- elimination-dispersal

A virtual bacterium is actually one trial solution (may be called a search-agent) that moves on the functional surface to locate the global optimum. A chemotactic step can be defined as a tumble followed by a tumble or a tumble followed by a run.

Let j be the index for the chemotactic step. Let k be the index for the reproduction step. Let l be the index of the elimination-dispersal event. Also, the following parameters are set before initializing the loops.

p: Dimension of the search space, 2
S: Total number of bacteria in the population
Nc : The number of chemotactic steps, S
Ns: The swimming length, gen
Sr: The number of bacteria reproduced per gen, S/2
Nre : The number of reproduction steps, gen
Ned : The number of elimination-dispersal events, gen/2
Ped : Elimination-dispersal probability, 0.5
C (i): The size of the step taken in the random direction specified by the tumble, unit vector.

Let P(j, k, l) { (j, k, l) | i 1,2,..., S}i = q = represent the position of each member in the population of the S bacteria at the j-th chemotactic step, k-th reproduction step, and l-th elimination-dispersal event. Here, let J (i, j, k, l) denote the cost at the location of the i-th bacterium.

The brief description of prime steps in BFOA is given below.

i) Chemotaxis: This process simulates the movement of an E.coli cell through swimming and tumbling via flagella. Biologically an E.coli bacterium can move in two different ways. It can swim for a period of time in the same direction or it may tumble, and alternate between these two modes of operation for the entire lifetime. Suppose (j, k, l)i q represents i-th bacterium at jth chemotactic, k-th reproductive and l-th elimination-dispersal step. C(i) is the size of the step taken in the random direction specified by the tumble (run length unit). Then in computational chemotaxis the movement of the bacterium may be represented by

$$\theta^{i}(j+1,k,l)=\theta^{i}(j,k,l)+C(i)\frac{\Delta(i)}{\sqrt{\Delta^{T}(i)\Delta(i)}} \tag{9}$$

Where Δ indicates a vector in the random direction whose elements lie in [-1, 1].

ii) Swarming: An interesting group behavior has been observed for several motile species of bacteria including E.coli and S. typhimurium, where intricate and stable spatio-temporal patterns (swarms) are formed in semisolid nutrient medium. A group of E.coli cells arrange themselves in a traveling ring by moving up the nutrient gradient when placed amidst a semisolid matrix with a single nutrient chemo-effecter. The cells when stimulated by a high level of succinate, release an attractant aspertate, which helps them to aggregate into groups and thus move as concentric patterns of swarms with high bacterial density. Determination of nutrient function [J_{health}] is done and accordingly positions of bacteria are sorted.

iii) Reproduction: The least healthy bacteria eventually die while each of the healthier bacteria (those yielding lower value of the objective function) asexually split into two bacteria, which are then placed in the same location. This keeps the swarm size constant. The Sr bacteria with the highest J_{health} values die and the remaining Sr bacteria with the best values split (this process is performed by the copies that are made are placed at the same location as their parent).

iv) Elimination and Dispersal: Gradual or sudden changes in the local environment where a bacterium population lives may occur due to various reasons e.g. a significant local rise of temperature may kill a group of bacteria that are currently in a region with a high concentration of nutrient gradients. Events can take place in such a fashion that all the bacteria in a region are killed or a group is dispersed into a new location. To simulate this phenomenon in BFOA some bacteria are liquidated at random with a very small probability while the new replacements are randomly initialized over the search space.

IV. SIMULATION RESULTS AND DISCUSSIONS

To evaluate and to compare the performance of the suboptimal PTS, numerous computer simulations have been conducted to determine the PAPR improvements. QPSK modulation is employed with N =128, 256 sub-carriers. The phase weighting factors W= 2, 4 have been used. In order to generate the Complementary Cumulative Distribution Function (CCDF) [13] of the PAPR, 10,000 random OFDM frames have been generated. The sampling rates for an accurate PAPR need to be increased by 4 times.

In fig.4, for number of sub-blocks, V=16 and N=128, the effect of change in number of generations [1, 5, 10, 20, 30, 40] is seen. The number of bacteria selected is 30 and the reduction is 5.65dB is noticed at 10^{-3} with g=40.

The same effect is seen for N=256 in fig.5. It is noticed that at g=1 to g=10, the reduction is of 0.7dB at 10^{-3}. Also for further increase is in number of chemotactic steps does not lead to much reduction.

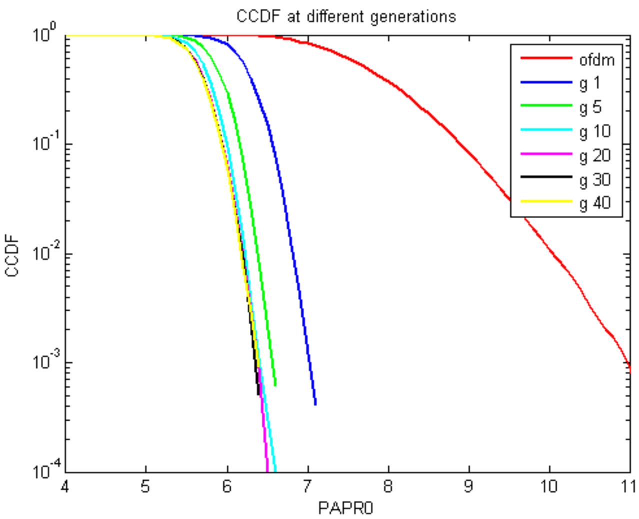

Fig.4 CCDF performance at different number of generations at N=256, W=4, V=16, S=30.

In table I, for various number of generations, PAPR performance at 10-3 for N=128 and 256 is seen. For every increase in generations from 1 to 10, there is noticeable reduction of PAPR. For further increase in generations, the reduction is almost the same. So, for this approach the number of generation selected is 10.

Table I- Comparison of performance at different number of generations

Number of generations, gen	Performance (PAPR at 0.001) at N=128	Performance (PAPR at 0.001) at N=256
1	6.56 dB	7 dB
5	6 dB	6.5 dB
10	5.78 dB	6.3 dB
20	5.75 dB	6.295 dB
30	5.73 dB	6.29 dB
40	5.7 dB	6.287 dB

Comparing with PSO, by taking same parameters [N=256, V=16, W=4], at number of generations 10 this approach gives 6.54dB reduction in PAPR at 10^{-4} and at gen=20 the reduction is 6.5dB where as in PSO it gives 7dB reduction. In table II, it is cleared that BFO gives better reduction than PSO with reduced number of generations.

Table II- Comparison of performance at different number of generations in PSO and BFO

Method	Generation, gen	Performance (PAPR at 0.001)
PSO[5]	30 dB	7 dB
BFO	10 dB	6.54 dB
BFO	20 dB	6.5 dB

Fig.5 shows the simulated results of the BFO assisted PTS technique, in comparison against normal OFDM for number of sub-blocks V. V is one of value in the set [2, 4, 8, 16, 32]. In particular, the PAPR of an OFDM signal exceeds 10.7 dB for 10^{-3} of the possible transmitted OFDM blocks. However, by introducing PTS approach with V=16 clusters partition with phase factors limited to W=2, the 10^{-3} PAPR reduces to 4.7 dB. In short, new approach can achieve a reduction of PAPR by approximately 5 dB at the10^{-3} PAPR. Thus, the performance of the techniques is better for larger V since larger numbers of vectors are searched for larger V in every update of the phase weighting factors. Moreover, it can be observed that probability of very high peak power has been increased significantly if PTS techniques are not used. As the number of sub-blocks and the set of phase weighting factor are increased, the performance of the PAPR reduction becomes better. However, the processing time gets longer because of much iteration. From fig.5, as expected, the improvement increases as number of clusters increases.

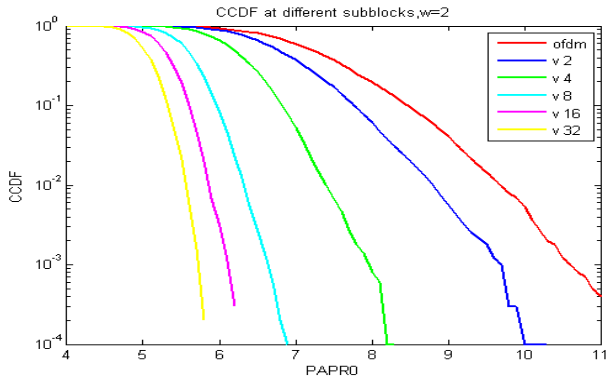

Fig.5 PAPR reduction performance for BFO algorithm, W=2, N=128, gen=10, S=30

The effect of increasing phase factors is also studied which is shown in fig.6.in this simulation, W is increased to 4 [1, -1, 1j, -1j]. By increasing number of phase factors the reduction is increased. The PAPR is reduced to 5.6 dB at 10^{-3}, so the reduction of 5 dB is achieved from the default OFDM signal.

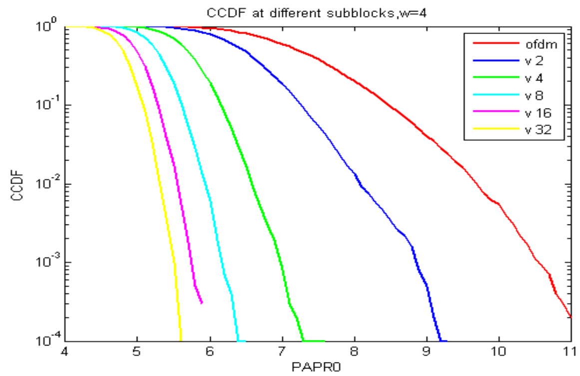

Fig.6 PAPR reduction performance for BFO algorithm N=128, S=30

In table III, the PAPR performance is analyzed at various sub-blocks and phase factors for population size 30. It is noticed that the performance at 10^{-3} is minimum at W=4, V=32 ie.5.4 dB and at W=2, V=32 i.e.5.2 dB. Thus, using the BFO technique, better results are obtained than the previous published work.

In table IV, the fair comparison of BFO assisted PTS scheme is done with other stochastic approaches by selecting N =128,V=8,W=4,and gen=10,S=30.The exhaustive search algorithm (ESA) [7], simulated annealing (SA) [6], Genetic algorithm (GA) [3] , Particle swarm optimization (PSO) [5], Electromagnetism (EM) [7] searching method to compare the performance of PAPR reduction with that of the BFO method. In the ESA, the selection of the phase factors is limited to a set of finite number of elements. The performance is analyzed at 10-3 and it is seen that with BFO the reduction is more than the other methods.

Table III- PAPR performance of proposed method at different sub-blocks

Number of sub-blocks,V	Number of Phase factors,W	Performance (PAPR 0.001) of other methods	Performance (PAPR 0.001) of proposed BFO method
8	2	PSO[5] – 6.6 dB	6.5 dB
16	2	PSO[5] - 6.1dB	6 dB
4	4	GA[3] – 7 dB	6.8 dB
8	4	SA[6]- 6.7 dB PSO[5]- 6.4dB GA[3]-6.49 dB EM[7]-6.3 dB	6.08 dB

Table IV-Comparison of PAPR performance of BFO assisted PTS technique with the published work at N=128

Number of sub-blocks, V	Phase factors, W	Performance (PAPR 0.001) at S=30
2 4	4 4	8.8 dB 6.8 dB
8	4	6.08dB
16	4	5.56 dB
32	4	5.4 dB
8	2	6.5 dB
16	2	6 dB
32	2	5.7 dB

In table V, the amount complexity is analyzed and in BFO there are 4 steps applied on each bacteria and it is given as Complexity=4*s*gen.

With reduced complexity of 1200 and 1600, the BFO approach shows reduced PAPR of 6.08 dB and 6.02 dB respectively than other published work. Therefore, the proposed BFO method can offer better PAPR reduction while keeping a low complexity.

Table V- Comparison of amount complexity and performance of BFO assisted PTS technique with the published work

method	Number of subcarriers	Amount computations	Performance (PAPR 0.001)
ESA[7]	128	48=65,536	6.54dB
SA[6]	128	1*3000=3000	6.7 dB
GA[3]	128	30*100=3000	6.49 dB
PSO[5]	128	30*100=3000	6.4 dB
EM[7]	128	30*40=1200 30*100=3000	6.43 dB 6.3 dB
BFO	128	4*30*10=1200 4*40*10=1600	6.08 dB 6.02 dB

V. CONCLUSION

The implementation of the proposed BFO algorithm also showed considerable decrease in PAPR value with the increase in the accuracy of OFDM system as compared with the already published work. The amount complexity when was compared and validated against the ordinary PTS approach was found to be less. Hence, BFO proves to be computationally efficient than ordinary PTS approach.

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