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Peak to Average Power Ratio Reduction using Modified Cuckoo Search Algorithm in MIMO-OFDM System

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ABSTRACT

Multiple input multiple output orthogonal frequency division multiplexing (MIMO-OFDM) is an attractive transmission technique for high bit rate communication systems. One of the major drawbacks of the MIMO-OFDM signals is the high Peak to Average Power ratio (PAPR) of the transmitted signal. 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. To improve the PAPR statistics of MIMO-OFDM signals further while still reducing the computational complexity, this paper proposes a new PTS using modified cuckoo search (MCS) algorithm. MCS-PTS algorithm can significantly reduce the computational complexity for larger PTS sub blocks and offers low PAPR at the same time. Simulation results show that the MCS-PTS algorithm is an efficient method in reducing the computational complexity of the conventional PTS and to achieve significant PAPR reduction.

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INTRODUCTION

Multiple input Multiple output Orthogonal frequency division multiplexing (MIMO-OFDM) is a widely used wireless communication system that requires a high bit rate and high capacity transmission (Cimini, 1985). Besides the advantages of the MIMO-OFDM system, one of the main drawbacks is the high peak-to average power ratio (PAPR) of the signal, which causes bit error rate (BER) performance degradation. In addition, the PAPR should be reduced for elimination of nonlinear distortion effects and for power efficiency of the high power amplifier (HPA) (Ryu *et al*., 2004, Saleh, 1984). To suppress this problem, many PAPR reduction methods have been developed in the literature, such as clipping (Neill and Lopes,1995), coding (Jones *et al*., 1994), selected mapping (SLM) (Auml *et al*., 1996), tone injection (TI) (Tellado,2000), tone reservation (TR),active constellation extension (ACE) (Krongold and Jones,2003), and partial transmit sequence (PTS) (Muller and Hubber,1997). Clipping is the simplest method for application, but it distorts the signal and decreases the BER of the system. TI, TR, and ACE do not distort the signal, but these methods cause energy increases of the transmitted signal. SLM neither distorts the signal nor causes energy increases in the signal, but its application is more complex than the others methods.PTS is a distortionless and efficient PAPR reduction method; for this reason, it is one of the most studied methods in PAPR reduction.

The PTS (Muller and Hubber,1997). 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 (Cimini and Sollenberger,2000) has the computational complexity linearly proportional to the number of subblocks. A neighborhood search is proposed in (Han and Lee, 2004) using gradient descent search. A suboptimal method (Tellambura,2001)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 (Wen *et al*., 2008). A suboptimal PTS algorithm based on particle swarm

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optimization is proposed in (Zhang, 2008). An intelligent genetic algorithm for PAPR reduction is developed in (Zhang, 2009).

In this paper, we propose a newly suboptimal phase optimization scheme based on modified cuckoo search (MCSPTS) 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 MCS-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 2, MIMO-OFDM system model is described. The modified MCS (MCS-PTS) algorithm is introduced and its application to PAPR problem is presented in Section 3. Simulation results and computational complexity of MCS-PTS are given in Section 4.Conclusions are made in Section 5.

2. MIMO-OFDM system model:

In MIMO-OFDM system, a number of antennas are placed at the transmitting and receiving ends and their distances are separated far enough. The idea is to use realize spatial multiplexing and data pipes by developing space dimensions which are created by multi-transmitting and receiving antennas. The transmitted signal bandwidth is so narrow that its frequency response can be considered as being flat [24]. Defining the channel matrix H as $N_r \times N_t$ complex matrix, the elements of it are fading coefficients from the j^{th} transmit antenna to the i^{th} receive antenna.

Assuming that a MIMO system with a transmit array of N_t antennas and a receive array of N_r antennas, the transmission can be expressed as

$$y=Hx+n \tag{1}$$

where, y is $N_r \times 1$ receiving vector, x is $N_t \times 1$ transmitting vector and n is additive white Gaussian noise with autocorrelation matrix ,$Rn=E\{nn^H\}=N0\ INT$, INT is an $N_t \times N_t$ identity matrix. N_0 is identical noise power of each receiving branch [25], [26].

2.1 PAPR of MIMO-OFDM signal:

A continuous- time complex envelope of the transmitted OFDM signal is given by

$$x(t) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} X_k e^{j2\pi f_k t} \quad ,0 < t < NT \tag{2}$$

where the input data vector is $\mathbf{X} = [X_0, X_1, \ldots X_{N-1}]$, and N is the number of subcarriers. Each symbol in X is mapped with quadrature amplitude modulation (QAM) and each symbol is assigned to one subcarrier at a frequency of $f_k = k\Delta f$, $0 \le k \le N-1$, where subcarrier spacing $\Delta f = 1/NT$ and T is the symbol period of one OFDM signal. However, PTS is required for discrete-time signals for PAPR reduction. For this reason, the discrete-time OFDM signal is given by

$$x(n) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} X_n e^{j2\pi kn/LN} \quad ,0 < N < LN \tag{3}$$

where L is the oversampling factor. OFDM signals are oversampled as L = 4 In this way, the value of the PAPR in the discrete-time is nearly the same as the PAPR in the continuous-time. The oversampled OFDM signal is transformed as $x = [x_0, x_1, \ldots, x_{LN-1}]$ and the PAPR of the discrete-time signal is expressed as

$$PAPR(x) = \frac{\max\limits_{0<n<LN-1}\{|x(n)|^2\}}{E\{|x(n)|^2\}} \tag{4}$$

where E {·} denotes the expected value of the OFDM signal. From equation (3) it is clear that maximum PAPR is equal to the number of subcarriers. Complementary cumulative density function (CCDF) is a commonly used performance criterion to show the PAPR reduction, and it is described as CCDF = $Pr\{PAPR(x) > PAPR_0\}$ where $PAPR_0$ is a certain level of PAPR. CCDF denotes the probability that the PAPR of the data symbol exceeds the given threshold and is given by

$$Pr\{PAPR(x) > PAPR_0\}=1-(1-e^{-PAPR_0})^N \tag{5}$$

Consequently the PAPR of MIMO-OFDM signals at each transmit antenna is written as (Jiang *et al.*, 2007)

$$PAPR_{MIMO-OFDM} = \max_{1<i<M_t} PAPR_i \tag{6}$$

where $PAPR_i$ denotes the PAPR of i^{th} transmit antenna. This can be further derived as

$$\Pr\{PAPR_{MIMO\text{-}OFDM} > PAPR_0\} = 1-(1-e^{-PAPR_0})^{M_t N} \quad (7)$$

From equation (7) CCDF of MIMO-OFDM is much less than in equation (5)

2.2 Partial Transmit Sequence for PAPR Reduction:

The block diagram of the PTS method is shown in Figure 1. In the MIMO-OFDM PTS, the input data vector **X** is encoded with space time encoder into two vectors X1 and X2.The data vector X1 and X2 are partitioned into V disjointed subblocks. Three partitioning methods have been proposed in the literature(Yang and Deb,2009), and we choose the random partitioning method, which provides the best PAPR reduction performance. The partitioned subblock **X** is denoted as

$$X = \sum_{m=0}^{M-1} X^m \quad (8)$$

The subblock vectors are oversampled by $(L-1)N$ zero padding to measure the continuous-time value of the PAPR. Oversampled subblocks are subjected to inverse fast Fourier transform (IFFT) operating with size LN and the subblocks are transformed into $x^m=[x_0^m, x_1^m, \ldots x_{LN-1}^m]$,$0<m<M-1$.Each subblock is rotated by phase factors $b_v = e^{j\varphi}$, where φ (0, 2π) , and finally the subblocks are summed. After the PTS operation, the OFDM signal becomes

$$x'(n) = \sum_{m=0}^{M-1} b_m x^m \quad (9)$$

The aim in the PTS is to find the optimal phase factors. In the phase optimization, because the phase factor of the first subblock is taken as $b_0 = 1$, there are W^{M-1} alternative b combinations, where $b = [b_1, b_2, \ldots, b_{M-1}]$ and W is the number of the phase factors. In sequence b, b_v values are as follows:

$b_v = \{\pm 1\}$ if W=2
$= \{\pm 1, \pm j\}$ if W=4
$= \{\pm 1, \pm j, +0.707 \pm 0.707j, -0.707 \pm 0.707j\}$ if W=8

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. Therefore, the side information (SI) consists of b and the length of the SI is $R = (M-1)\log_2(W)$ bits.

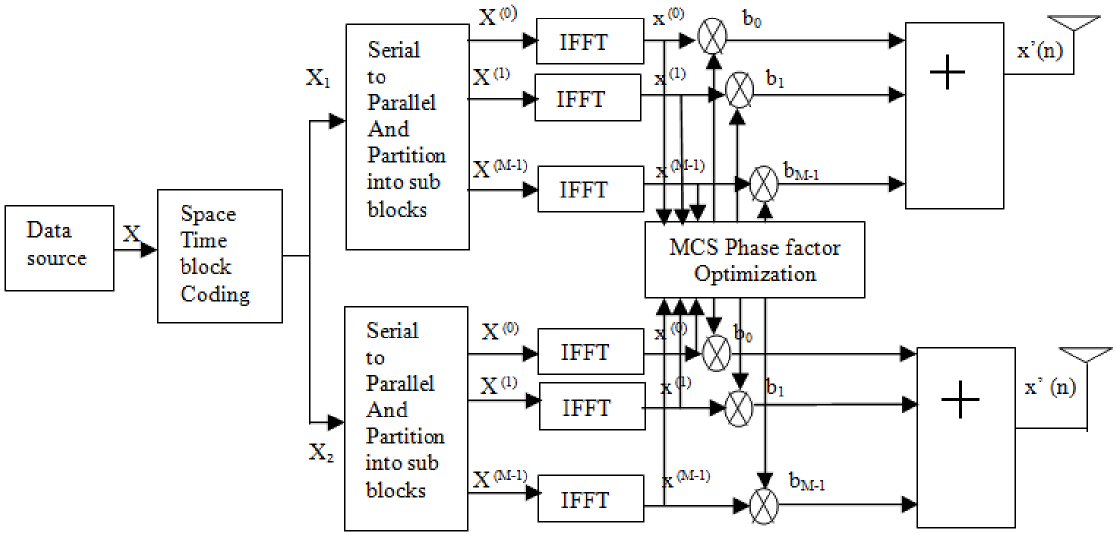

Fig. 1: Block Diagram of MCS-PTS model.

3. Minimize PAPR using Modified Cuckoo Search (MCS) Algorithm:

In order to get the OFDM signals with the minimum PAPR, a suboptimal combination method based on the modified cuckoo search (MCS) algorithm is proposed to solve the optimization problem of PTS. The modified MCS algorithm with lower complexity can get better PAPR performance. The minimum PAPR for PTS method is relative to the problem:

Australian Journal of Basic and Applied Sciences, 7(13) November 2013, Pages: 32-42

Minimize

$$f(b) = \frac{\max\{|x'(b)|^2\}}{E\{|x'(b)|^2\}} \quad (10)$$

subject to $b \in \{e^{j\varphi m}\}^M$ (11) where $\varphi m \in \frac{2\pi k}{W}$,k=0,1,…..W-1

3.1 .Cuckoo Search (CS) Algorithm:

Cuckoo Search is a metaheuristic search algorithm which has been proposed recently by (Yang and Deb, 2010). The algorithm is inspired by the reproduction strategy of cuckoos. At the most basic level, cuckoos lay their eggs in the nests of other host birds, which may be of different species. The host bird may discover that the eggs are not its own and either destroy the egg or abandon the nest all together. This has resulted in the evolution of cuckoo eggs which mimic the eggs of local host birds (Pavlyukevich,2007). To apply this as an optimization tool, (Yang and Deb, 2010) used three idealized rules:

1) Each cuckoo lays one egg, which represents a set of solution co-ordinates, at a time and dumps it in a random nest;

2)A fraction of the nests containing the best eggs, or solutions, will carry over to the next generation;

3) The number of nests is fixed and there is a probability that a host can discover an alien egg. If this happens, the host can either discard the egg or the nest and these results in building a new nest in a new location.

The steps involved in the CS are then derived from these rules and are shown in Algorithm 1 . An important component of a CS is the use of Lévy flights for both local and global searching. The Lévy flight process, which has previously been used in search algorithms (Viswanathan,2008), is a random walk that is characterized by a series of instantaneous jumps chosen from a probability density function which has a power law tail. This process represents the optimum random search pattern and is frequently found in nature (Bratton and Kennedy, 2007). When generating a new egg in CS algorithm, a Lévy flight is performed starting at the position of a randomly selected egg, if the objective function value at these new coordinates is better than another randomly selected egg then that egg is moved to this new position. The scale of this random search is controlled by multiplying the generated Lévy flight by a step size a. For example setting a = 0.1 could be beneficial .The use of Lévy flights as the search method means that the CS can simultaneously find all optima in a design space and the method has been shown to perform well .

Algorithm 1: Cuckoo Search (CS):

Initialize a population of n host nests x_i, i = 1,2,. . . ,n
for all x_i *do*
Calculate fitness $F_i = f(x_i)$
end for
while Number Objective Evaluations < MaxNumberEvaluations
do
Generate a cuckoo egg (x_j) by taking a Lévy flight from random nest
$F_j = f(x_j)$
Choose a random nest i
if ($F_j > F_i$) then
xi $\leftarrow$ xj
Fi $\leftarrow$ Fj
end if
Abandon a fraction pa of the worst nests
Build new nests at new locations via Lévy flights to replace nests lost
Evaluate fitness of new nests and rank all solutions
end while

3.2 .Modified Cuckoo Search (MCS) Algorithm:

Given enough computation, the CS will always find the optimum (Yang and Deb,2010) but, as the search relies entirely on random walks, a fast convergence cannot be guaranteed. Three modifications to the method are made with the aim of increasing the convergence rate, thus making the method more practical for a wider range of applications but without losing the attractive features of the original method.

The three modifications are:

1) In the CS, α is constant whereas the MCS, the value of α decrease as the number of generations G increase. This is done to encourage more localized searching as the individuals, or the eggs, get closer to the solution. An

Australian Journal of Basic and Applied Sciences, 7(13) November 2013, Pages: 32-42

initial value of the Lévy flight step size A = 1 is chosen and, at each generation, a new Lévy flight step is calculated using $\alpha = A/\sqrt{G}$, where G is the generation.
2) In the CS, there is no information exchange between individual nests and, fundamentally, the searches are performed independently. Therefore, adding up information exchange between the eggs tries to formulate convergence to minimum. In the MCS, after discover probability P_d is applied the nests with the best fitness are arranged into a group of top nests up to S position on n nests. For each of the top nests, a second nest in the available nests is picked at random and a new nest is then generated.
3) The third modification done in this MCS is restriction of the nest which participated in a generation with worst solutions or eggs. In the CS, there is no restriction to the nests which have worst solutions. Thus the useless nest in the next generation made search complexity of the CS increases. In MCS, reduction of worst nest is applied to begin the next generation and search complexity gets decreased as compared with the CS.

Algorithm 2: Modified Cuckoo Search (MCS):

A $\longleftarrow$ MaxLévy Step Size
ϕ $\longleftarrow$ Golden Ratio
P_d $\longleftarrow$ Discover Probability
$P_s = 1 - P_d$ Select Probability
S $\longleftarrow$ Split Position
Initialize a population of n nests $x_i (i = 1,2,. . . ,n)$
for all x_i do
    Calculate fitness $F_i = f(x_i)$
end for
Generation number G $\longleftarrow$ 1
while $G \leq G_{max}$ do
  G $\longleftarrow$ G + 1
  Sort nests by order of $f(x_i)$
  Discard the last nest
  So, n = n –1
  $S = P_s * n$
  for i = S + 1 : n do
  Current position x_i
  Calculate Lévy flight step size $\alpha = A/G^2$
  Perform Lévy flight from x_i to generate new egg x_k
   $x_i \longleftarrow x_k$
   $F_i \longleftarrow f(x_i)$
  end for
  for i = 1: S *do*
   Current position x_i
   Pick another nest from the top nests at random x_j
   if $x_i = x_j$ then
    Calculate Lévy flight step size a A/G^2
   Perform Lévy flight from x_i to generate new egg x_k
    $F_k = f(x_k)$
    Choose a random nest l from all nests
    if $(F_k > F_l)$ *do*
     $x_l \longleftarrow x_k$
     $F_l \longleftarrow F_k$
    end if
   else
    $dx = | x_i - x_j |/\phi$
 Move distance dx from the worst nest to the best nest to find x_k
    $F_k = f(x_k)$
    Choose a random nest l from all nests
    if $(F_k > F_l)$ then
     $x_l \longleftarrow x_k$
     $F_l \longleftarrow F_k$
    end if
   end if
  end for
end while

3.3 .MCS Algorithm to reduce PAPR:

Here MCS algorithm is applied to search the better combination of phase factor for PTS. In the paper, we select the phase factor b = $\{-1, 1\}^M$ or **b** =$\{-1, 1, j,-j\}^M$ or b=.$\{\pm1, \pm j, +0.707\pm 0.707j, -0.707\pm 0.707j\}^M$. In the proposed MCS-PTS technique we optimize the best phase factor from W^{M-1} combinations where M is number of sub-blocks and W is the allowed phase factor. In the MCS-PTS algorithm, the available nests represents the phase vector, b = $\{b_{i1}, b_{i2}, b_{i3}, \ldots, b_{i\ WM-1}\}$, i = 1,.. W^{M-1}. where M-1 denotes the size of a randomly distributed initial population. In MCS-PTS the objective is to find the minimum of fitness P (b_i) i.e, the optimum phase factor combination for which the PAPR is minimum. The phase factor P (b_i) is equivalent to the fitness function $F_i= f(x_i)$ in the MCS algorithm which is to be minimized. The mathematical model for MCS-PTS is derived for finding the best phase factor combination which has low PAPR. For reducing the computational complexity and PAPR using MCS algorithm, the following steps are followed.

1. Initially the set of possible phase factor combinations is identified as the available nests.
2. The objective is to find the best phase factor combinations with minimum number of searches for which the peak to average power ratio have a minimum value.
3. The discover probability (P_d) of alien eggs is assigned a value in the range [0, 1] to competently have the minimum no. of searches.
4. From the available phase factor combinations, 'n' values are initialized and their fitness i.e. PAPR value is calculated.
5. The next step of MCS is the generation (G).In the first generation the n initialized phase factors are sorted by their PAPR values in the descending order and the least value is discarded. So the 'n' initialized phase factor values are reduced to n-1 values.
6. The discover probability P_d is then applied to the n-1 phase factor values and the values are splitted using the split position S= (Ps*n), where Ps = 1 – P_d . Ps is the split function in which the phase values are splitted.
7. The phase factor values up to the split position S were placed into top position and the phase values from S+1 to n – 1 were placed in the bottom position. By considering the bottom phase values in the next step, each of them were replaced by new phase factor value using Lévy flight.

7) Lévy flight is used to generate the new phase factor value using Max Lévy step size A. Lévy flight elects a new phase value with maximum Lévy step size A ϵ [0, 3].The process is repeated until the bottom values are replaced by new phase factor values.

8. The generation of top phase factor values is slightly different from the bottom nests. The first phase factor value with its PAPR value will be compared with the PAPR value of the randomly chosen phase factor value from the available phase factor combination. If the new PAPR value is less than the existing PAPR value then the existing value is replaced by the new value. In case if both the new and existing values are same, the Lévy flight step is applied to choose randomly the new phase factor value and then it was updated by comparing its PAPR value. Once all the phase factors contributes for generating the new phase factor combination via MCS–Lévy flight, then the phase factor with the best PAPR values are placed in the next generation.
9. One generation is completed after all the top phase factor values are compared with the new phase factor values. Then Step 5 to Step 9 is repeated until n –1 generations are completed
10. The optimum phase factor combination producing least PAPR value is obtained once the n-1 generations were completed. The computation complexity of the proposed MCS-PTS algorithm is calculated as (n*G)/2.

Using MCS-PTS algorithm the best PAPR value is optimized in minimum number of searches. Thus the proposed MCS-PTS efficiently reduces the computation complexity to optimize the best PAPR with less computational complexity.

4. Simulation Results:

To evaluate and compare the performance of the MCS-PTS algorithm for MIMO-OFDM PAPR reduction, numerous simulations have been conducted. In order to get CCDF, 1000 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= 4,8,16 &32 are chosen, the similar simulation results can be obtained, while the performance will be better.

In Figures 2.1&2.2, some results of the CCDF of the PAPR are simulated for the MIMO-OFDM system with 256 subcarriers, in which M = 8&16 subblock employing random partition and the phase weight factor W =2&4, uniformly distributed random variables are used for PTS. As we can see that the CCDF of the PAPR is gradually promoted upon increasing the numbers of generations due to the limited phase weighting factor. As the numbers of generation are increased, the CCDF of the PAPR has been improved. For a generation Gn = 34 & 41, we can see that the MCS based PTS technique is capable of attaining a near OPTS technique performance, when $Pr(PAPR > PAPR_0) = 10^{-2}$.

In Figures 2.1&2.2, we compare the PAPR performance of different numbers of generations Gn. Basically, the PAPR performance is improved with the increase in Gn. However, the degree of improvement is limited when Gn is above 30. On the other hand, the computational complexity is increased with Gn. Only a slight improvement is attained for increasing Gn = 20 to 40. The computational complexity of Gn = 40 is double of that of Gn = 20. Hence, based on the trade-off between the PAPR reduction and computational complexity, Gn = 20 is a suitable choice for our proposed MCS based PTS technique.

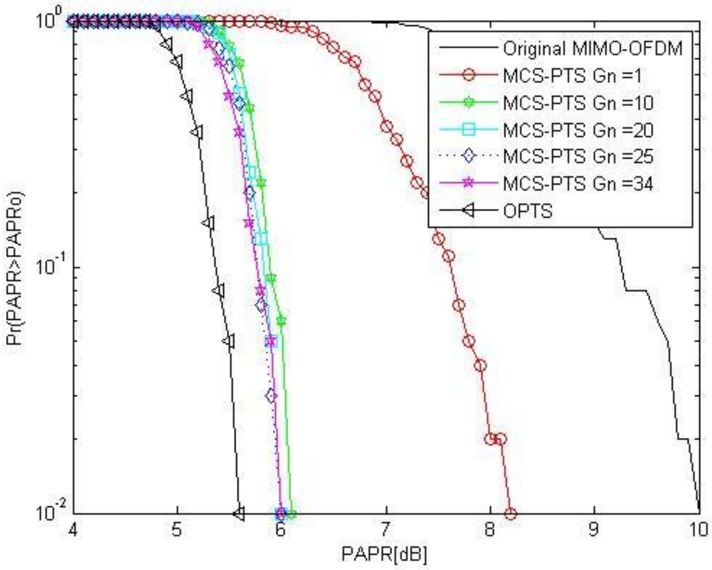

Fig. 2.1: CCDF of MCS technique for different Gn when M = 8 W= 4.

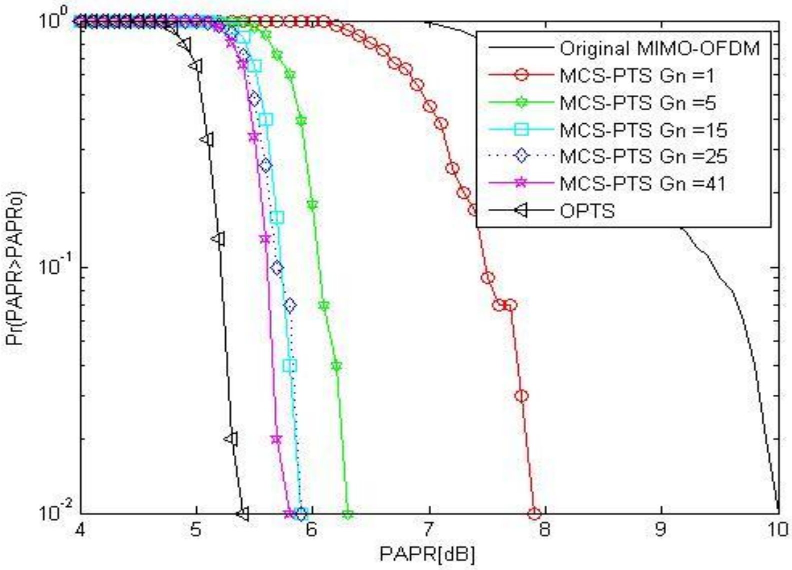

Fig. 2.2: CCDF of MCS technique for different Gn when M=16&W=2.

Figure 3 shows the simulated results of the MCS assisted PTS technique, in comparison against normal MIMO-OFDM for number of subblocks M.M is one of value in the set{2, 4, 8,16}. In particular, the PAPR of an MIMO-OFDM signal exceeds 10 dB for 10^{-2} of the possible transmitted MIMO-OFDM blocks. However, by introducing PTS approach with M= 16 clusters partition with phase factors equal to the number of subblocks, the 10^{-2} PAPR reduces to 5.7 dB. In short, new approach can achieve a reduction of PAPR by approximately 4.3dB at the10^{-2} PAPR. Thus, the performance of the techniques is better for larger M since larger numbers of vectors are searched for larger M 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 subblocks 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

Australian Journal of Basic and Applied Sciences, 7(13) November 2013, Pages: 32-42

much iteration. From Figure 3, as expected, the improvement increases as number of clusters increases. Thus, using the MCS technique, we can obtain better results than presented previously.

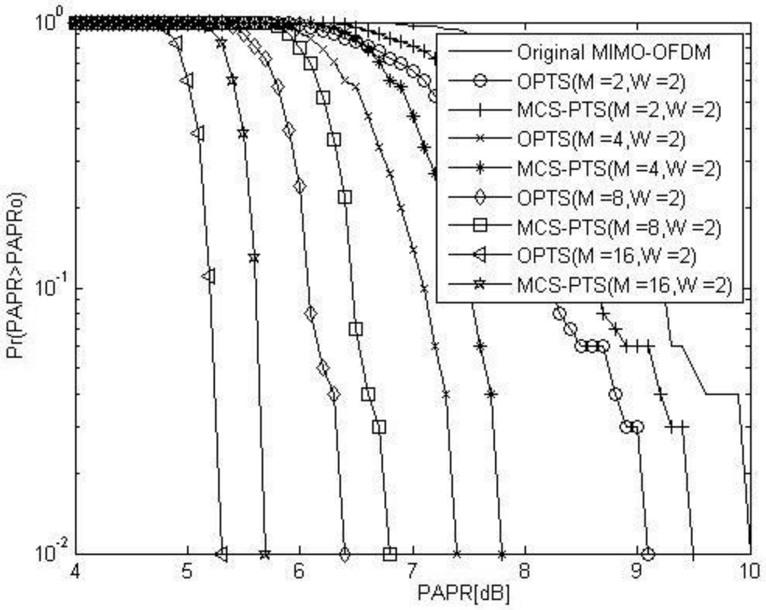

Fig. 3: CCDF of the PAPR with the PTS technique searched by MCS technique when N = 256, M = 2, 4, 8 and 16.

In Figures 4.1 to 4.3, for a fixed number of clusters, the phase weighting factor can be chosen from a larger set of {2, 4, 8, 16, 32}. It is shown that the added degree of freedom in choosing the combining phase weighting factors provides an additional reduction. When the number of phase weighting factor W= 4 and number of subblocks M= 2, PAPR can be reduced about 1.4 dB at 10^{-2} from 10.2 dB to 8.8 dB. When W= 4 and M= 4, at 10^{-2} PAPR can be reduced about 1.7 dB from 9.2 dB to 7.5 dB. When W= 4 and M= 8, at 10^{-2} PAPR can be reduced about 4 dB from 9.8 dB to 5.8 dB. As the number of subblocks 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.

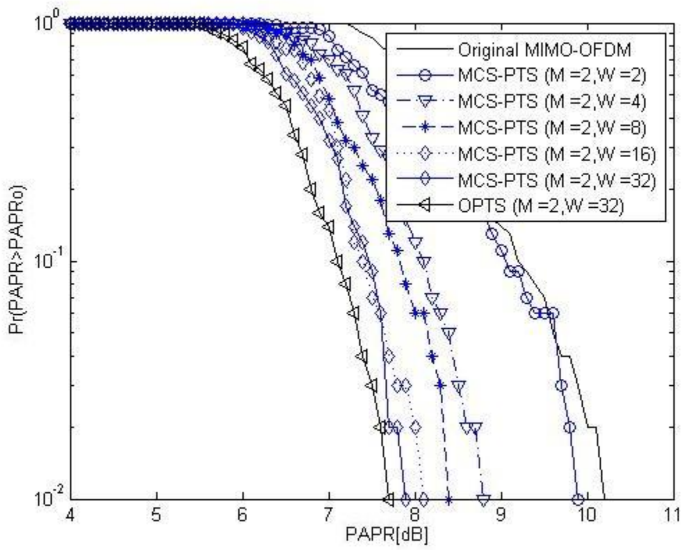

Fig. 4.1: Comparisons of MCS-PTS technique under different phase weight factors and M=2 subblock.

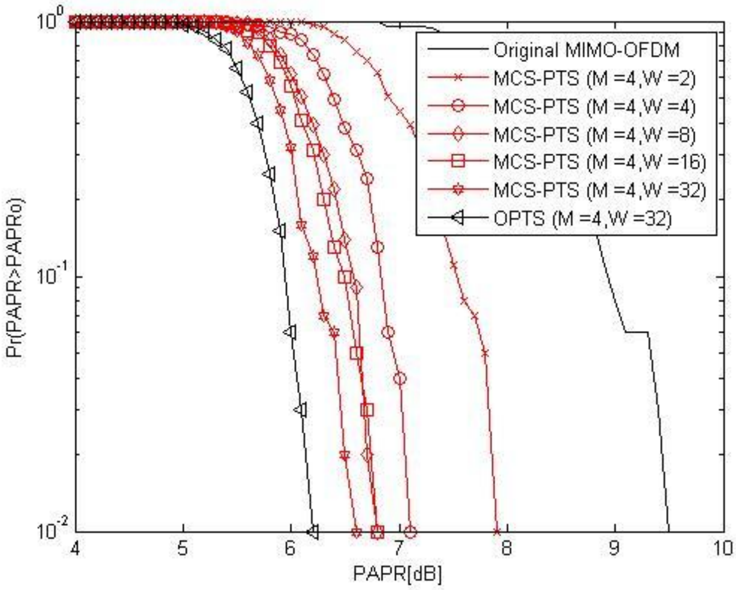

Fig. 4.2: Comparisons of MCS-PTS technique under different phase weight factors and M=4 subblock.

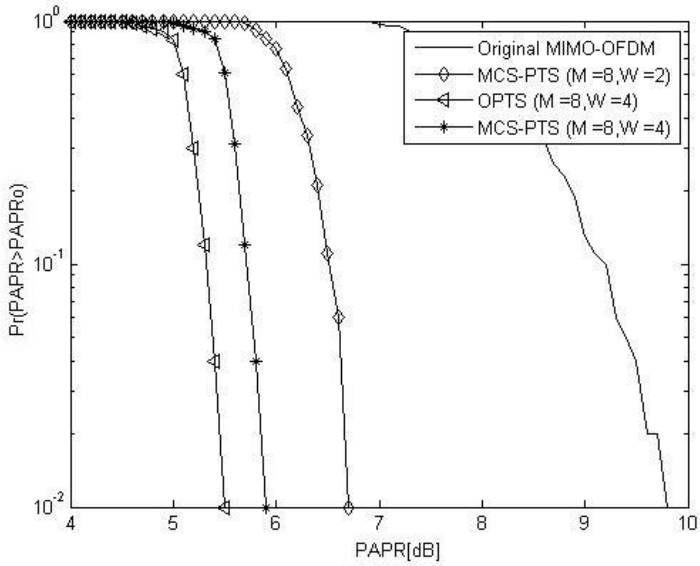

Fig. 4.3: Comparisons of MCS-PTS technique under different phase weight factors and M=8 subblock.

The iteration number of proposed technique is shown in Table 1.

Table 1: The computational complexity comparisons of MCS-PTS technique and OPTS under different phase weight factors and number of subblocks.

Combinations	OPTS		MCS-PTS	
	Computational Complexity (W^{M-1})	PAPR (db)	Computational Complexity (N*(N+1))/2	PAPR (db)
W=2 ,M=8	256	6.4	55	6.8
W=2, M=16	32,768	5.3	861	5.7
W=4 ,M=8	16,384	5.5	630	5.9
W=16 ,M=4	4096	6.3	435	6.7
W=32, M=4	32768	6.2	1176	6.6

For M= 16 & W=2 the OPTS technique requires 32,768 iterations per OFDM frame, while MCS-PTS technique requires 861 iterations only .The complexity of MCS- PTS is only 0.03% (861/32768) of that of the optimal PTS technique. For M= 14 & W=32 the OPTS technique requires 32,768 iterations per OFDM frame, while MCS-PTS technique requires 1176 iterations only. The complexity of MCS- PTS is only 0.04%

(1176/32768) of that of the optimal PTS technique. The iteration number of the proposed technique for other combination of phase weight factors and number of subblocks are also shown in Table 1.

In Figure 5, we compare the PAPR performance for various values of searches for W=2 and M=8 combination. Basically, the PAPR performance is improved with the increase in the number of searches. Here optimal combination (OPTS) of searching all the phase factors requires W^{M-1} searches which is equal to 128 searches. However, MCS-PTS require only 55 searches (N=10) to obtain a PAPR of 6.7 db at 10^{-2} which is 0.3 db greater than the optimal PAPR value of 6.4 db and 3.5 db less than the original MIMO-OFDM. The computational complexity is significantly reduced and it is reduced more for higher combinations which involve more number of searches.

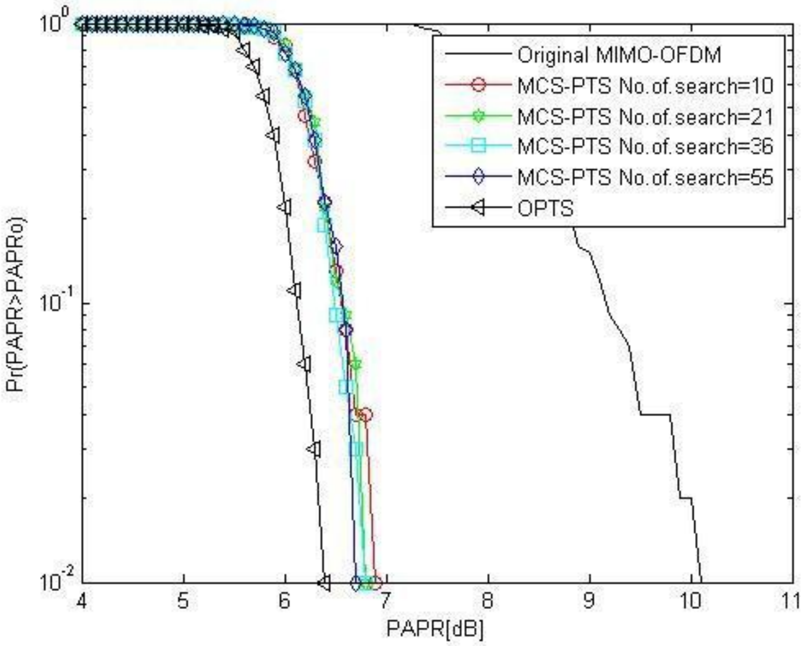

Fig. 5: CCDF of MCS technique for various searches when M = 8, W= 2.

7. Conclusion:

In this paper, we formulate the phase weighting factors searching of PTS as a particular combination optimization problem and we apply the MCS technique to search the optimal combination of phase weighting factors for PTS to obtain almost the same PAPR reduction near to that of optimal PTS while keeping low complexity. Simulations results show that MCS-based PTS method is an effective method to compromise a better tradeoff between PAPR reduction and computation complexity. By appropriate selection of phase weighting factors according to the required performance and tolerable complexity, the proposed MCS-PTS can give better PAPR reduction with less complexity. Additionally, the performance of the proposed method was slightly degraded compared to that of optimum method, PTS. However, the computational complexity of the proposed method was remarkably lower than that of optimum method.

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