Reducing Complexity in PTS Scheme using Optimization Techniques to reduce PAPR in OFDM Systems

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Abstract: OFDM is a technique used to combat Inter Symbol Interference (ISI) in wireless communication systems. OFDM offers high reliable data rate over frequency selective channels. But the drawback is high Peak to Average Power Ratio (PAPR) which will affect the power amplifier in the RF front end. Partial Transmit Sequence (PTS) has proven to be the efficient technique to minimize the PAPR in OFDM systems and it does not affect the Bit Error Rate (BER) much. But PTS in turn suffers from high search complexity. The optimization algorithms can offer a tradeoff between the search complexity and PAPR reduction. In this work the phase factor optimization in PTS scheme is converted into a one dimensional optimization problem. Genetic Algorithm (GA), Simulated Annealing (SA) and Particle Swarm Optimization (PSO) are applied to the problem defined. They are also compared in terms of PAPR reduction and complexity. The fitness functions are chosen according to the optimization technique.

Key Words: Genetic Algorithm (GA), Low complexity PTS, OFDM, PAPR reduction, Partial Transmit Sequences (PTS), PSO, SA

1. INTRODUCTION

OFDM is a powerful modulation technique used to reduce Inter Symbol interference (ISI) in wireless communication systems. It gives better performance in frequency selective fading environments. But the major problem of OFDM systems is high PAPR. Numerous methods have been discussed in literature to minimize the PAPR. But most of the techniques either increase the complexity of the system or deteriorates its bit error rate (BER) performance.

Designing an algorithm to reduce PAPR without affecting the BER performance and increasing the complexity is a great challenge. Among various techniques PTS technique has proved to be the best scheme in terms of PAPR reduction and PTS scheme does not deteriorate the BER performance much. But PTS increases the complexity of the system. Hence various techniques have been proposed to reduce complexity in PTS scheme. The optimization algorithms such as genetic algorithms (GA), particle swarm optimization (PSO), simulated annealing (SA) can be employed to reduce the so called search complexity in PTS technique. All these algorithms give only sub-optimal solution for the phase factor optimization problem in PTS and hence reduce the PAPR value. But the complexity of PTS is decreased when they are employed for phase factor optimization.

In [1] the overview of PAPR reduction schemes is given. The complexity and description of PTS are studied from [1]. In [2] a reduced complexity PTS algorithm with only two weighting factors \{1, \text{−}1\} is proposed. In [3] the signals at the middle stages of an N-point radix FFT using decimation in time (DIT) or decimation in frequency (DIF) are considered for sub-block partitioning. The computational complexity is further decreased by a method known as decomposition PTS (D-PTS) in [3]. In [4], it is discussed that generation of cost function $Q_n$ is based on addition the power of samples in time-domain at time n in each sub-block. As associated with conventional PTS pattern, the technique discussed in [4] attains nearly the similar PAPR reduction performance with reduced computational complexity.
In [11] genetic algorithm based PTS schemes are proposed. It uses the reciprocal of PAPR as fitness function. In [13] Simulated Annealing based PTS is given where the fitness function is the difference between the PAPR and desired value. In [14] Particle Swarm Optimization (PSO) based PTS is proposed where each phase factors are updated using the velocity equations. In [15], compressive sensing approach is discussed to reduce PAPR and BER is preserved. Joint Iterative filtering and companding is presented in [16] to mitigate PAPR with reduced computational complexity. In [17], PPAR better performance is achieved by addition of mapping signal to the OFDM signal.

2. SYSTEM MODEL AND PROBLEM DEFINITION

2.1 Definition of PAPR

PAPR of an analog signal \( x(t) \) is the ratio of its maximum power to its average. It is given by (1).

\[
PAPR[x(t)] = \frac{\max|x(t)|^2}{\mathbb{E}[|x(t)|^2]} \tag{1}
\]

Suppose \( s(t) \) is a continuous OFDM signal obtained after the A/D converter. The PAPR of \( s(t) \) can be estimated using the samples before the A/D converter. It is shown in [8] that the PAPR of the discrete OFDM sequence is a better estimate of that of the continuous signal after Analog to Digital converter when it is up-sampled by a factor of \( L \geq 4 \). The discrete OFDM signal PAPR is denoted as (2)

\[
PAPR[x(n)] = \frac{\max|x(n)|^2}{\mathbb{E}[|x(n)|^2]} \tag{2}
\]

Where \( x(n) = [x[0], x[1], \ldots, x[N-1]] \) and \( N \) is the number of sub-carriers i.e., number of OFDM symbols in one block. For simulation purposes the (2) is applied to \( x(n) \) after up-sampling it.

2.2 Complementary Cumulative Distribution function

PAPR reduction schemes do not give the same percentage of PAPR reduction for different inputs. So a useful quantity called CCDF is well-defined. It is the complement of the cumulative distribution of the PAPR i.e., probability that the PAPR will be greater than a given value \( PAPR_0 \). If a scheme is better than any other scheme in PAPR reduction sense then its CCDF curve will be to the left of the other. In the simulation results the CCDF of the PTS and GAPTS will be compared. It is given by (3)

\[
CCDF(PAPR_0) = P(PAPR > PAPR_0) \tag{3}
\]

2.3 Partial Transmit Sequences (PTS)

PTS is a probabilistic method which is widely found in many research works [2], [3], [4], etc. The PTS method is depicted in Fig 1. The PTS method partitions N symbol input data to \( V \) number of disjoint sub blocks as shown:

\[
X = [X^0, X^1, X^2, \ldots, X^{V-1}]^T \tag{4}
\]

Here, \( X^i \) are known as sub blocks which are of same size and are successively situated. Then each portioned sub block can be multiplication with the complex phase factor \( b^v = e^{j\phi_v}, = 1,2, \ldots, V \), after applying the IFFT to provide

\[
x = \text{IFFT}\left\{ \sum_{v=1}^{V} b^v X^v \right\} = \sum_{v=1}^{V} b^v \cdot \text{IFFT}\{X^v\}
\]
here $\{x^v\}$ is known as PTS. The selection of phase vector in such a way that PAPR is minimized and it is denoted as

$$[b^1, ..., b^V] = \arg\min \left( \max_{n=0,1,\ldots,N-1} \left| \sum_{v=1}^V b^v x^v[n] \right| \right)$$

The PAPR vector is in time domain is denoted as

$$\tilde{x} = \sum_{v=1}^V \tilde{b}^v x^v$$

In common, the choice on the phase factors $\{b^v\}_{v=1}^V$ is restricted to a set of values to diminish complexity of searching. The allowable phase factors can be denoted as

$$b = \left\{ e^{j2\pi i} \right\}_{i=0,1,\ldots,W-1}$$

The computational complexity of searching rises in exponential manner with rise in amount of sub-blocks. The PTS method needs $V$ IFFT processes to every data set and Roof $(\log_2 W^V)$ bits of side data. The PAPR value of PTS technique is modified by both number of sub-blocks and sub-block partitioning. The three different methods for sub block dividing are adjacent, interleaved, and pseudo-random. Out of these, the best result is obtained through pseudo-random method.

![Block diagram of Partial Transmit Sequence technique.](image-url)

3. PROBLEM FORMULATION

The objective of this work is to reduce the complexity while minimizing the PAPR by choosing appropriate $b^1, b^2, ..., b^V$ given by

$$PAPR\{x(b^1, b^2, ..., b^V)\} = \max \frac{\left| x(b^1, b^2, ..., b^V) \right|^2}{\mathbb{E} \left[ \left| x(b^1, b^2, ..., b^V) \right|^2 \right]}$$
Ordinary PTS gives the optimal solution for the above problem but has high search complexity. The optimization algorithms discussed in this paper aim at finding the optimal solution for (9) with less complexity. They provide a trade-off between the complexity and PAPR reduction.

Equation (9) is a V dimensional optimization problem. Since the phase factors can take only discrete values, a whole number $B$ in $[0, W^{V-1}]$ can be assigned to a particular phase vector $b = [e^{-2\pi\phi_1}, e^{-2\pi\phi_2}, ..., e^{-2\pi\phi_V}]$ such that $\phi_1, \phi_2, ..., \phi_V$ is the base V representation of the number $B$ i.e., $(B)_{10} = (\phi_1 \phi_2 ... \phi_V)_V$. Where $\phi_1, \phi_2, ..., \phi_V$ are the digits of the baseV number. Hence the V dimensional optimization problem is now converted into a one dimensional problem.

4. GENETIC ALGORITHM BASED PTS (GAPTS)

In this technique the phase optimization is done using genetic algorithm. It is a population based method. Though it gives sub-optimal phase factors its search complexity is less than the traditional PTS. The transmission of side information is required in GAPTS.

4.1 Fitness function

Normally when Genetic Algorithm is employed for PTS the fitness function $F$ for a fixed $X$ is chosen as the reciprocal of PAPR of the sequence $x$ combined using the particular possible set of phase factors $b^1, b^2, ..., b^V$.

$$F(b^1, b^2, ..., b^V) = \frac{1}{\log_{10} \text{PAPR}[x(b^1, b^2, ..., b^V)]} \quad (10)$$

Which can be converted into one dimensional function as $b^1, b^2, ..., b^V \rightarrow B$ and hence

$$F(B) = \frac{1}{\log_{10} \text{PAPR}[x(B)]} \quad (11)$$

Where $B \in [0, W^{V-1}]$. The reciprocal of PAPR is taken to convert the minimization problem to maximization problem. Now objective is to minimize the objective function. The search space is the set of all possible $W^{V-1}$ phase factors. In this work the fitness function is modified as $F_1$ which is given by (11)

$$F_1 = F + \lambda(F - \mu) \quad (12)$$

Where $\mu$ and $\lambda$ are the parameters. The maxima and minima of $F$ and $F_1$ occur for the same values of $B$ because

$$\frac{dF_1}{dB} = (1 + \lambda) \frac{dF}{dB}$$

4.2 simple three step genetic algorithm:

A simple three step genetic algorithm is given below

1) Initialization.
2) Reproduction.
3) Cross-over.
4) Mutation.
5) Count=Count+1.
6) If Count<G. Go to step 2)
7) Stop.
4.3 Initialization and coding:
Suppose if W=4 and V=4. Then there are four phase factors given by b = [1, j, -1, -j]. If we fix \(b^1 = 1\). Then there are \(W^{V-1} = 64\) possibilities of choosing four phase factors among the four available phase factors. So 7-bit binary code is assigned to all the possible phase factor sets. Initial population of some size P is chosen. For example if P=4, four random distinct binary strings are chosen and their fitness values are calculated using (11). This set of strings in the initial population is subjected to reproduction, cross-over and mutation. After these three steps we will get the new population which is again subjected to the three steps. This process is repeated till the number of generation is reached.

4.4 Reproduction:
Mean of the fitness values of the population are calculated and each fitness value is divided by the total value. Based on these values a roulette algorithm is used to obtain the reproduced population. There are many ways to implement roulette algorithm in software.

One is to obtain the Expected count of all the strings and round off them as
\[
\text{count}(k) = \text{Round}(\text{fitness}(k) / \text{mean}_\text{fitness})
\]
where ‘k’ is the population index. The new population contains the \(k^{th}\) string count(k) times after reproduction. It is possible that the sum of all the count values is not equal to the population size. In that case if the sum is less than population size, some random candidates are chosen to bring the sum of count values equal to the population size. If the sum is greater than population size then those number of minimum valued candidates are dropped.

4.5 Crossover and mutation:
The strings are paired randomly. A position is chosen randomly and the bits after that positions are exchanged between the chosen pair. Random numbers can be generated in software (For example using function randi in MATLAB). In hardware pseudo random numbers can be generated using linear feedback shift registers. Mutation is the random flipping of bits. There are few problems in using GA with PTS. The PAPR objective function is too complicated having too many peaks. GAPTS gives suboptimal solution. Hence its PAPR performance is less compared to conventional PTS.

5. Simulated Annealing Based PTS (SAPTS)
In SAPTS the phase factor optimization is done using simulated annealing algorithm. It is a nature inspired meta-heuristic optimization algorithm. Simulated Annealing algorithm uses a steady reduction in the probability of accepting poorer solutions as it discovers the solution space. Accepting poorer solutions is a basic behavior of Meta-heuristics as it permits for a additional widespread search for the best solution [13].

5.1 Simulated annealing algorithm:
It is an iterative procedure which stops after the stopping criterion is met. The temperature is initialized to a value and decremented in every iteration using a cooling schedule which is a function of iteration variable. It the temperature becomes less than the \(T_{\text{stop}}\) the algorithm is stopped. In every iteration, a random new solution is chosen and its fitness value is calculated. If the new fitness value is greater than that of the previous solution the new solution is accepted. Else if the acceptance probability is larger than a random number in (0,1) the new solution will be accepted. The acceptance probability is also a function of the iteration variable

Initialize \(T_0\), \(T_{\text{stop}}\), C, D, h, α and β
\[k = 1\]
Choose the initial solution as \(\vec{b} = [1 \ 1 \ 1 \ 1 \ ...]\)
Calculate \( \hat{f} = f(\tilde{b}) \)

While \((T(k) > T_{\text{stop}})\)

\[ k = k + 1 \]

\[ T = T(k) \quad // \text{Update } T \text{ according to the cooling schedule} \]

Perturbation is used to obtain a new solution \( \tilde{b} \)

Calculate \( \hat{f} = f(\tilde{b}) \)

\( \Delta E = \hat{f} - \hat{f} \)

If \((\Delta E < 0)\)

\[ \tilde{b} = \tilde{b} \]

\[ \hat{f} = \hat{f} \]

Else

Generate an uniform number \( r \) in \((0,1)\)

Calculate the transition acceptance probability \( \text{Prob} \)

If \((\text{Prob} > r)\)

\[ \tilde{b} = \tilde{b} \]

\[ \hat{f} = \hat{f} \]

End if

End while

5.2 Fitness function and search space:

The fitness function \( F \) for a fixed \( X \) is the \( \text{PAPR} \) of the sequence \( x \) combined using the particular possible set of phase factors \( b^1, b^2, ..., b^V \).

\[
    x(b^1, b^2, ..., b^V) = \sum_{i=1}^{V} b^i \text{IFFT}(X^i) \quad (13)
\]

\[
    F(b^1, b^2, ..., b^V) = \log_{10} \text{PAPR} \left[ x(b^1, b^2, ..., b^V) \right] \quad (14)
\]

\[
    \text{PAPR}(x(b^1, b^2, ..., b^V)) = \max_{E} \frac{|x(b^1, b^2, ..., b^V)|^2}{E[|x(b^1, b^2, ..., b^V)|^2]} \quad (15)
\]

Now objective is to minimize the objective function. The search space is the set of all possible \( W^{V-1} \) phase factors.

5.3 Cooling schedule:

SA is an iterative algorithm which runs using a cooling schedule. Cooling schedule is essentially a function of the iteration variable. The temperature is initialized to a value and it is slowly decremented using the cooling schedule. When the temperature reaches a predefined value called \( T_{\text{stop}} \) the algorithm stops. The cooling schedule used in this work is in equation (4).

\[
    T(k) = T_0 \exp \left( -C \sqrt{k} \right) \quad (16)
\]

Where \( T_0 \) is the initial temperature. \( C \) and \( D \) are parameter. \( C \) and \( D \) are chosen as 0.98 and 2 respectively [13]. For a given number of iterations ‘k’ we can determine the value of \( T_{\text{stop}} \) for a given \( T_0 \) using (4).

5.4 Perturbation:

This is the technique used to obtain the new candidate solution. Perturbation essentially generates the new solution using some distribution. Since the phase factors can only take discrete values a whole number \( B \) in \([0, W^{V-1}]\) is assigned to each possible phase factors \( b = [e^{j2\pi\phi_1}, e^{j2\pi\phi_2}, ..., e^{j2\pi\phi_V}] \) such that \( \phi_1, \phi_2, ..., \phi_V \) is the base V representation of the decimal
number i.e., \((B)_{10} = (\phi_1 \phi_2 ... \phi_V)_{10}\). In this work perturbation is done using discrete uniform distribution. A random number in \([0, W_V-1]\) is generated and converted into equivalent phase vector.

### 5.5 Acceptance probability:

The acceptance probability is decreasing function of the iteration variable \(k\). Hence the probability that the bad solution will be accepted in the successive iterations decreases. The acceptance probability used in this work is given by (5)

\[
Prob(k) = \left[1 - \frac{h.\Delta E}{T(k)}\right]^{\frac{1}{h}} \tag{17}
\]

### 6. PARTICLE SWARM OPTIMIZATION BASED PTS (PSOPTS)

PSO is a computational method which provides the best solution for a given problem by iteratively trying to provide candidate solution with respect to quality. The general particle swarm optimization is given below [14].

Let \(f: \mathbb{R} \rightarrow \mathbb{R}\) be the cost function that is to be reduced. The PSO algorithm is as follows:

- For every particle \(i = 1, ..., S\) do:
  1. Set the location of particle \(x_i \sim U(b_{lo}, b_{up})\), here \(b_{lo}\) and \(b_{up}\) represent the boundaries of the search space.
  2. Reset the particle’s best recognized position to its original location: \(p_i \leftarrow x_i\)
  3. If \(f(p_i) < f(g)\), set the group’s best location: \(g \leftarrow x_i\)
  4. Reset the speed: \(v_i \sim U(-|b_{up} - b_{lo}|, |b_{up} - b_{lo}|)\)

Until a termination criterion is met repeat:

- For each particle \(i = 1, ..., S\) do:
  1. Pick random numbers: \(r_p, r_g \sim U(0,1)\)
  2. For each dimension \(d = 1, ..., n\) do:
     - Update the particle’s velocity using
     \[
     v_{i,d} \leftarrow \omega v_{i,d} + c_p r_p (p_{i,d} - x_{i,d}) + c_p r_g (g_d - x_{i,d})
     \]
  3. Set speed of particle: \(x_i \leftarrow x_i + v_i\)
  4. If \(f(x_i) < f(p_i)\) do:
     - set best recognized location of the particle: \(p_i \leftarrow x_i\)

- At this moment, \(g\) shows the best identified result.

#### 6.1 Problem formulation for PSO PTS:

The cost function used is the PAPR itself. The discrete phase factors are assigned with a whole number as given by (14). Hence the dimension is one and the search space is discrete. The updated velocities are rounded off before adding them to the previous solution.

### 7. SIMULATION RESULTS

Simulations are done in MATLAB. The complementary cumulative distribution function (CCDF) of PTS, GAPTS, SAPTS and PSOPTS schemes are obtained which is shown in figs (2-5). The details of the simulations are as follows. Number of sub carriers = 64. Number of iterations = 3000. (3000 independent data sets are generated randomly). Modulation used: 16QAM. Number of sub-blocks \(V = 4\). Number of possible phase factors \(W = 4\). Population size \(N_p = 4, 6, 8\) and Number of generations \(N_g = 4, 5, 8\) for GA and PSO. For SA the parameters \(C\) and \(D\) are chosen as 0.98 and 2 respectively. For PSO the acceleration constants \(c_1\) and \(c_2\) are chosen as 2.3 and 1.6 respectively and
ω = 0.4 The CCDF graphs for various schemes and various complexities are given in the following figures. Fig 2 shows the CCDF graphs of GAPTS for different complexities. These graphs are compared with the normal PTS and OFDM system which does not employ any PAPR reduction technique. From Fig. 2 it is evident that GA provides a tradeoff between complexity and PAPR reduction. Increasing the complexity further may improve the PAPR performance but the limit of complexity is $W^V-1$. If we increase the complexity further then we won’t get the advantage of using an Optimization Algorithm. The CCDF graph for this limiting case ($Ng \times Np = W^V-1$) is plotted for reference. It corresponds to $Ng = 8, Np = 8$. Similarly the CCDF graphs are of SAPTS and PSOPTS for various complexities are given in Fig.3 and Fig.4 respectively.

All the three schemes provide a trade-off between PAPR reduction and complexity. Fig. 5 shows the CCDF graphs of GAPTS for the two different fitness functions fit1 and fit2 given by (11) and (12) respectively. It is clear that using the proposed fitness function the PAPR performance is increased. Finally all the three schemes for same complexity using the corresponding fitness functions are compared in Fig. 6 which shows that SAPTS performs well for the given set of parameters. The fitness function chosen for GAPTS for this comparison is (12).

![Fig. 2. Comparison of various complexities](image)

![Fig. 3. Comparison of various complexities](image)
CONCLUSION

SAPTS has high PAPR performance compared to the other schemes for same complexity. Normal PTS has high PAPR performance but also high computational complexity. There are many other techniques to reduce complexity in PTS. Most of them have less PAPR performance. A few modifications can be made in these algorithms to improve its PAPR performance.

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