Reduction of PAPR in OFDM Signals by using Electromagnetism Optimization Algorithm

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Abstract: Orthogonal Frequency Division Multiplexing grown to be a trendy modulation process inside impressive tempo wirelesscommunications. It is more advantageous over remaining technologies, even though it has some problems also. The high PAPR (Peak toAverage Power Ratio) is the main difficulty which causes non linearity at the receiving end. To reduce the PAPR so many techniques areproposed in previous such as clipping and filtering, SLM, CE, SA, PTS and so on. PTS (Partial Transmit Sequence) is highly successive thananother. In this paper PTS technique is used to reduce the PAPR but there is one problem with PTS technique, it introduces a high amount of complexity. So that to reduce such complexity and get better PAPR we planned to implement a novel based stochastic optimization algorithm which is EM (Electromagnetism-like) algorithm. By using EM get the better PAPR than PTS

.

***Key words*:** OFDM, PAPR, PTS (Partial Transmit Sequence), EM (Electromagnetism -like) algorithm

1 .Introduction

Orthogonal Frequency Division Multiplexing (OFDM) earlier far and wide, worn with an array of digital transmissions together with digital audio/video broadcasting, digital subcarrier lines, along with wireless local area networks [3] for the reason that of its facility to survive with the frequency selective fading of wideband communication through reasonable complexity. Yet, one foremost problem allied by OFDM is its high peak-to-average power ratio (PAPR).

Various methods for reducing PAPR have been proposed for OFDM system, such as deliberate clipping [4], partial transmit sequences [5-7], selective mapping [8], block coding [9] and sub carrier scrambling [10], and the rest. Within intentional clipping, the uncomplicated method, signals is intentionally clipped sooner than amplify. Even though various methods to PAPR decreasing keep in review [11], it is at rest really desirable to present a Overall review as well as several inspirations of Peak to average power ratio reductions, such that power discount, plus to be balanced through several classic systems of PAPR reduction throughout the hypothetical investigation in addition to simulation. In code, selecting, the amount of codes amid small PAPR presented be restricted and the ensuing PAPR cannot be actually undersized. Selected level mapping (SLM) multiples a frequency field signal via prearranged arbitrarily produced vectors furthermore go for surrounded by them the vector to present the time-domain character amid lowly PAPR. Partial Transmit Sequence (PTS) is the basis of the equivalent idea like SLM. On the other hand, it recommends PAPR reduction workability. Inside this idea, sub-carriers are divided into multiple disjoint sub-blocks. After that, the phase of every one sub-block is modified with phase rotation factors to construct PAPR as low as possible. PTS broadly develops PAPR appearance, other than crucially; investigate the best possible phase weighting factors explore from every permutation of proper phase weighting factors. It revolves exposed to investigate complication increases exponentially amid the sum of sub blocks. On the way to diminish the vital complication and avoid/reduce the custom of side information, numerous additions of Partial transmit sequence built-up just now [12]. Legendary stochastic methods designed for PAPR make smaller consist of the Genetic algorithm (GA) [13] besides particle swarm optimization [14]. Established going on past gatherings, state that assessment to employ an original PTS technique carry on the EMO algorithm to decrease the PAPR of OFDM signals throughout this paper. The simulations construct obvious that the proposed EMO not only attain a massive PAPR reduction other than enjoy complication rewards judge against amid the additional familiar stochastic processes [15-18].

The rest of this paper is organized as follows. In Section 2, Background is given. In Section 3, PAPR reduction techniques are explained theoretically. In Section 4 is simulation results, section 5 is the conclusion.

2. Back ground

PAPR Problem: Think about an OFDM system consisting of N subcarriers. Let a vector $\boldsymbol{X}$=[$X0$, $X1$, ⋯, XN-1] indicate the input data in an OFDM block. Every symbol in X is worn to modulate a associate carrier. Allow to f_k, k=0,1, …., N-1, indicate the k^{th} subcarrier frequency. In the OFDM scheme, the subcarriers should be elected to be orthogonal, and this way $f_k = k.\ \Delta\ f$, anywhere $\Delta f=1/(NT)$ and T is the symbol period. For that motive, the resulting complex baseband signal can be expressed as

$$x(t) = \frac{1}{\sqrt{N}} \sum_{k=o}^{N-!} X_k\, e^{j2\pi k \Delta f}, \qquad 0 \le t < NT. \qquad (1)$$

PAPR is taking apart as the fraction of the maximum to the average Power throughout an OFDM symbol period. For x (t), we consequently have

$$\text{PAPR} = \frac{\max_{0 \le t < NT} \left[\, |x(t)|^2 \right]}{P_{av}} \qquad (2)$$

Where P_{av} is the average power of $x(t)$.

In practice, the greater part systems operation with a discrete-time signal, therefore we have to sample the continuous-time signal $x(t)$. **B**ecause the Nyquist rate sampling probably misses a quantity of signal peaks, oversampling by a factor of L is worn to inaccurate the true PAPR of $x(t)$, where L is an integer larger than 1. The L-time oversampled signal can be known as

$$x_n = \frac{1}{\sqrt{N}} \sum_{k=o}^{N-1} X_k\, e^{j2\pi nk/(LN)} \quad n=0,1,\ldots..LN-1 \qquad (3)$$

Where the oversampling factor $L \geq 4$ in a realistic OFDM system. From (3), the L-time oversampled samples can be obtained by performing LN-point inverse discrete Fourier transform (IDFT) on the data block $\boldsymbol{X}$ with $(L-1)N$ zero padding. For the discrete-time signal x_n, the PAPR can be formulated the similar as

$$\text{PAPR} = \frac{\max_{0 \le n \le NL-1} [|x_n|^2]}{E(|x_n|^2)} \qquad (4)$$

Where E(·) denotes the expected value. From the central limit theorem, it follows that for large value of N (in general, $N \geq 64$), both the real and the imaginary parts of xn are Gaussian distributed. Therefore, the amplitude $|xn|$ has a Rayleigh distribution. Therefore, the cumulative distribution function (CDF) of $|xn|$ is given by

$$F(\zeta) = Prob\{|xn| \le \zeta\}$$

$$= \int_0^{\zeta} \frac{2y}{\sigma^2} exp\left(-\frac{y^2}{\sigma^2}\right) dy$$

$$= 1 - exp\left(-\frac{\zeta^2}{\sigma^2}\right) \quad , \quad \zeta > 0 \qquad (5)$$

Where $\sigma^2 = E[|x_k|^2]/2$ .from equation (5) we can find the OFDM signals have a high PAPR value.

The complementary cumulative distribution function (CCDF) is one of the most frequently used performance measures of for PAPR reduction, representing the probability than the PAPR of an OFDM symbol exceeds the given threshold $PAPR0$, which is denoted as

CCDF= P (PAPR>$PAPR0$).

3. PAPR Reduction techniques

In this paper we are using two reduction techniques, those are following below.

1. Partial transmit sequence (PTS)
2. Electromagnetism optimization algorithm (EMO).

3.1. Partial Transmit Sequence (PTS)

The partial transmit sequence (PTS) technique partitions an input data block of M symbols into V disjoint sub blocks as follows:

$$X^{(m)} = [X_0^{(m)},. X_1^{(m)} \ldots X_{N-1}^{(m)}] \qquad (6)$$

And the sub blocks are combined to minimize the PAPR in time domain. The L times oversampled time domain signal of X_m Concatenated with (L -1) N Zeros. These are called the partial transmit sequences. Complex phase factors, $b_m = e^{j\theta_m}$,m=1, 2, •••, M, are introduced to combine the PTSs. The set of phase factors is denoted a vector b = $[b_1, b_2, \ldots, b_m]^T$

$$X_k^{(m)} = \begin{cases} X_k, if\ X_k \subset X^{(m)} \\ 0, X_k \not\subset X^{(m)} \end{cases} , \qquad (7)$$

Such that

$$X = \sum_{m=1}^{M} X^{(m)} \qquad (8)$$

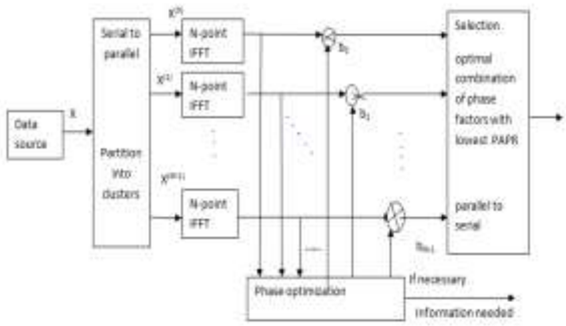

Fig .1: Block diagram of PTS technique for PAPR reduction

The above Fig .1 represents the block diagram Partial Transmit Sequence. The PTS technique requires V IFFT operations for each data block and $[\log_2 W^V]$ bits of side information. The PAPR performance of the PTS technique is affected by not only the number of sub blocks, V, and the number of the allowed phase factors, W, but also the sub block Partitioning. In fact, there are three different kinds of the sub block partitioning schemes: adjacent, interleaved, and pseudo-random. Among these, the pseudo-random one has been known to provide the best performance.

As discussed above, the PTS technique suffers from the complexity of searching for the optimum set of phase vector. In the literature, various schemes have been proposed to reduce this complexity.

3.2. Electromagnetism Optimization Algorithm

Electromagnetism Optimization algorithm is a population based algorithm that has been planned to explain regular problems successfully. In common, EMO imitates the attraction and repulsion system of electromagnetism assumption that is founded on Coulombs law. Every element symbolizes a result, in addition to the charge of every element relays to its object function value. On iteration k, a population amid *M* positions is produced. Every result position is measured as a position in a multidimensional result liberty with an assured charge. This charge is allied to the objective function values linked through all the result positions. In the subsequent, utilize the EMO technique to investigate the best possible phase factor intended for the PTS method in order to diminish the PAPR. The process of the proposed EMO algorithm can be described as follows:

Step.1. *Initialization:* Here initially, solution length will be definite just as the fitness function. instantly, definite the higher and lower limits in every length. Moreover, the population range P_{Max} should be definite within involving EMO algorithm to the optimization of phase weight factor sequence. similar to the bulk stochastic algorithms, the EMO method begins amid producing *M* random sample positions or points $\{\{\theta_{m,v}^{k}\}_{v=1}^{V}\}_{m=1}^{M}$Since the sufficient area, wherever *V* is the length of the problem (i.e., V means number of sub-blocks) as well as $\theta_{m,v}^{k}$ indicates the n^th^ coordinate of the point *m* of the population at iteration *k*. Equivalent to electromagnetism optimization, every point $\theta_m^k = \{\theta_{m,v}^k\}_{v=1}^{V}$ is considered as a nearly charged point that is free in the space. It should be renowned that in a multidimensional solution space everyplace all points symbolizes a result; a charge is allied amid every point. As such, every coordinate of a point, indicated as $\theta_{m,v}^{k}$, is intended by

$$\theta_{m,v}^{k} = l_v + \lambda (u_v - l_v)$$

Where u_v is the higher limit of the *v –th* length; l_v is the lower limit of the v-th length; and λ is a uniform random number creator inside [0, 1].

Step.2. *Determination of fitness function and bounds:* In this study, we use the position and weight as parameters to compute the fitness function of each particle, i.e., given a point (i.e., phase factor vector *W*) θ_m^k , the fitness function, defined as the amount of PAPR reduction, can be expressed as

$$\boldsymbol{f}(\theta_m^k) = 10 \log_{10} \frac{\max |x'(\theta_m^k)|^2}{E[|x'(\theta_m^k)|^2}.$$

When the *M* points are all identified, the point with the best objective function value is stored into $\theta_{best,}^{k} = \{\theta_{best,v}\}_{v=1}^{V}$. As we are interested in the values of phase factors in the range of 0 to 2*Π*, the upper bound and lower bound are set to 0 and 2 *Π*, respectively.

Step.3. *Local search and update:* Local search should be able to find a better solution in theory. Local search is used to gather the neighborhood information for a sampled point, which can be applied to one point or to all points in the population for local refinement at each iteration. Theoretically, the local search is expected to find a better solution.

Step.3.1) Calculate maximum feasible step length s_{max} based on the parameter $\delta \epsilon [0; 1]$, where the maximum feasible step length can be computed using the following equation:

$$\delta_{max} = \left(\max_{1 \le t < NT} (u_v - l_v) \right)$$

Step 3.2) Generate a candidate of point $\breve{\theta} = \{\breve{\theta}_v\}_{v=1}^{V}$ A new particle Θ is generated from the current best point *best*. As is a small random change coming from $\breve{\theta}_{best}^{k}$ Here, we randomly change two coordinates to generate. Where the modified coordinate of the current best point, denoted as $\breve{\theta}_v$ is computed using the following equation:

$$\breve{\theta}_v = \theta_{best,v}^{k} + \boldsymbol{\lambda} . \delta_{max}$$

Step.3.3) Decide whether to update the current best point $\breve{\theta}_{best}^{k}$: If the new point $\breve{\theta}$ observes a better point, the sample point $\breve{\theta}_{best}^{k}$: is replaced by this new point $\breve{\theta}$

Step.3.4) Repeat Step 3.1 to Step 3.3 until the maximum number of local search iteration is met.

Step.4. *Calculation of charge:* The particle moves according to Coulomb's force produced among the particles, as we assign a charge-like value to each particle. The charge of each particle is determined by its fitness function value, which can be evaluated as: the artificial charge q_m^k at point θ_m^k is determined by the fitness function value, and is calculated using the following equation:

$$q_m^k = exp\left\{ -V \frac{f\theta_m^k) - f(\theta_{best,}^k)}{\sum_{m=1}^{M} [f\theta_m^k) - f(\theta_{best,}^k)]} \right\}$$

By observing above equation, we can find that 1) a large $\boldsymbol{f}(\theta_m^k)$ results in a small $q_m^k$and vice versa; and 2) the artificial charges are all positive. Now, the problem on hand is how to determine the force of attraction or repulsion between each pair of particles $\theta_m^k$and θ_r^k Suppose that $f(\theta_m^k) < f(\theta_r^k)$, which implies that $q_m^k > q_r^k$ in this case, the one that has better fitness function value is preferred, that is θ_m^k is the preferred point and particle θ_r^kshould be attracted" to particle θ_m^k That means the particle attracts other particles with better with better fitness function values and repels other particles with fitness cost function values.

Step.5. *Calculation of resultant force:* The resultant force among particles determines the effect of the optimization process. The resultant force of each particle can be evaluated by Coulomb’s law and the superposition principle as: determining the charge of each point on $= \{\theta_m^k\}_{m=1}^{M}$ and defining the rule of attraction-repulsion mechanism of artificial charge the force vector, $F_{m,r}^{k}$,between two points θ_m^k ,*m* and θ_r^k ,is computed as

$$F_{m,r}^{k} = \begin{cases} (q_m^k - q_r^k) \frac{q_m^k . q_r^k}{||q_r^k - q_m^k||^2}, if\ f(\theta_r^k) \ge f(\theta_m^k), (repulsion) \\ (q_r^k - q_m^k) \frac{q_m^k . q_r^k}{||q_r^k - q_m^k||^2}\ , if\ f(\theta_r^k) < f(\theta_m^k), (attraction) \end{cases}$$

The total force $\wp_m^k$ exerted on each point θ_m^k by the other (*M* -1) points are then calculated by

$$\wp_m^k = \sum_{\substack{r-1 \\ r\neq m}}^{M} F_{m,r}^k,\ m=0,\ 1,\ \ldots M\text{-}1$$

Step.6. *Movement of the particles:* After calculating the total force $\wp_m^k$ the point *m* is updated in *v-th* coordinate of the force by the force by a random step length as given as

$$\theta_{m,v}^{k+1} = \begin{cases} \theta_{m,v}^k + \lambda \frac{\wp_{m,v}^k}{||E_m^k||}(u_v - \theta_{m,v}^k), if \wp_{m,v}^k > 0 \\ \theta_{m,v}^k + \lambda \frac{\wp_{m,v}^k}{||E_m^k||}(\theta_{m,v}^k - u_v), if \wp_{m,v}^k \leq 0 \end{cases}$$

Step.7. *Criterion:* Running the EM-like procedures until the predetermined iteration or the allowable optimal value is met. In other words, the procedures will be terminated as the criterion is reached.

4. Results and discussions:

*R*educe PAPR in OFDM signals by using an optimization algorithm is shown in table no: 1.

	Original PAPR in (DB)	*PTS PAPR in (DB)*	*EM PAPR in (DB)*
64 carriers	*10.7*	*5.3*	*4.1*
128 carriers	*11*	*7.0*	*6.0*
256 carriers	*13.0*	*10.9*	*9.5*

Table no:1 Comparison between Original, PTS ,EM Peak to Average Power Ratio for different carriers.

From the table, we observe, EM algorithm obtains less PAPR with low complexity. Figure 2 shows the CCDF as a function of PAPR distribution when PTS method is used with 64 numbers of subcarriers. Figure 3 shows the same result for 128 number of sub carriers. M takes the value of 4. It is easy to see that the PAPR reduction efficiency. In Fig.2, PAPR can be reduced about 5.3dB from 10.9dB to 8.8dB. In Fig.3, when M=4, PAPR can reduce 7.0dB from 11.0dB to 9.5dB.

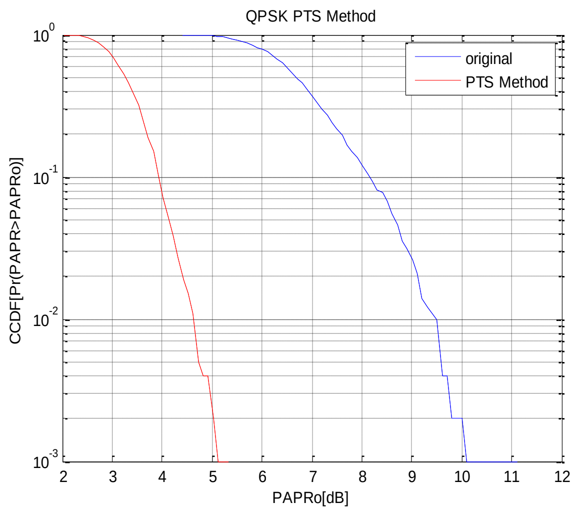

Fig 2: 64 bit process on PTS-PAPR reduction in MIMO-OFDM channel

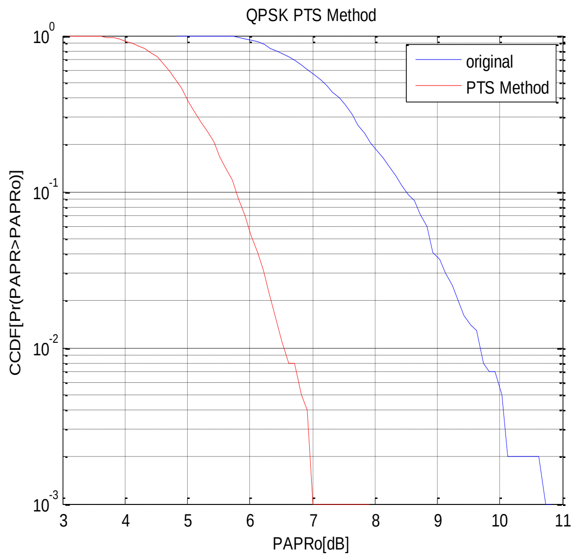

Fig 3: 128 bit process on PTS-PAPR reduction in MIMO-OFDM channel

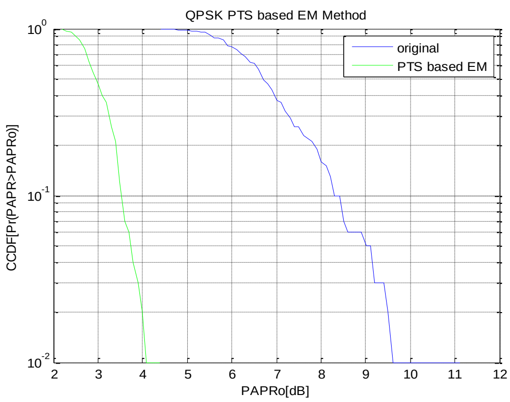

Fig 4: 64 bit process on EM-PAPR reduction in MIMO-OFDM channel

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Figure 4 shows the CCDF as a function of PAPR distribution when EM method is used with 64 numbers of subcarriers. Figure 5 shows the result for 128 number of sub carriers. M takes the value of 4. It is easy to see that the PAPR reduction efficiency. In Fig.4, PAPR can be reduced about 4.1dB from 10.9dB to 8.8dB. In Fig.5, when M=4, PAPR can reduce 6.0dB from 11.0dB to 9.5dB.

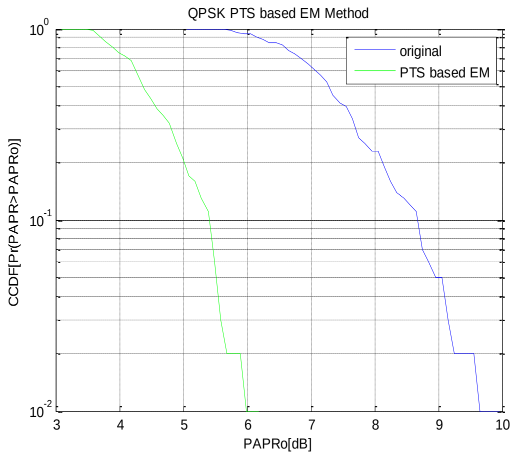

Fig 5: 128 bit process on EM-PAPR reduction in MIMO-OFDM channel

Figure.6 represents comparison of PTS and EM. It can easy to say which the best method for PAPR reduction is. It shows that the EM method go ahead to less significant average PAPR than the other stochastic methods. Here EMO and PTS methods get the PAPR values for 64 carriers is 4.1dB, 5.3dB and for 128 carriers is 6.0dB, 7.0dB respectively.

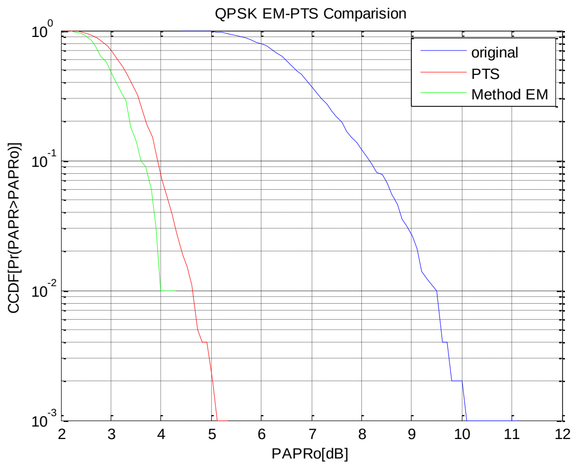

Fig 6: PAPR reduction of EM and PTS methods for 64 carriers

5. Conclusion

Inside this paper, we examined an efficient PAPR reduction technique committed to OFDM signals using EM algorithm. The EM method obtains the less PAPR i.e. 4.1dB compared to PTS technique, and also decreases the complexity. While the computational complexity diminishing ratio enlarges as the amount of sub-carriers enlarges, the planned method grow to be more relieve intended for the high data rate OFDM systems .

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