Scaled Offset PSO based PTS for PAPR Reduction in OFDM systems

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***Abstract*— In this paper, an improved scheme called Scaled Offset Particle Swarm Optimization based Partial Transmit Sequence (SOPSO-PTS) for reducing Peak-to-Average Power Ratio (PAPR) in wireless communications is presented. The main focus of this paper is to reduce PAPR as well as the computational complexity. The proposed scheme SOPSO-PTS has salient features such as faster convergence to the optimum value and provides a good control mechanism to the particle's velocity which makes it unique from the other conventional PSO-PTS schemes. The proposed scheme performs better when compared to Simulated Annealing (SA) PTS and Particle Swarm Optimization (PSO) PTS techniques.**

Keywords—Orthogonal Frequency Division Multiplexing, Partial Transmit Sequence, Quadrature Amplitude Keying, Particle Swarm Optimization.

I. Introduction

In Orthogonal Frequency Division Multiplexing (OFDM), closely spaced orthogonal sub-carriers carry data on various parallel channels. This in turn maintains high data rate transmission [1]. OFDM is used in various applications such as Digital Audio Broadcasting (DAB), Digital Video Broadcasting (DVB), Digital Subscriber Line (DSL), World Wide Interface for Microwave Access (Wi-MAX) and Wide Local Area Networks (WLAN). OFDM seems to be attractive with various advantages such as high spectral efficiency, multipath delay spread tolerance, and immunity to fading, power efficiency and its robust nature to fading conditions. One of the main issues in OFDM systems is its large PAPR. High PAPR results from the non-linear distortion, spectral re-growth, and inter-symbol interference (ISI) [2-3].

PAPR Reduction Techniques can be classified broadly into three major categories such as Signal Distortion, Multiple Signaling and Probabilistic and Coding Techniques. Signal Distortion technique distorts the signal before passing through the power amplifier (PA) thereby reducing PAPR. In Multiple Signaling and Probabilistic techniques, various permutations of OFDM signal are generated and the one with the lowest PAPR is selected for transmission. Coding Techniques focuses on PAPR reduction with additional features such as error detection and error correction.

Clipping and Filtering, Peak Windowing, Companding, and Peak Cancellation are some types of signal distortion techniques. Partial Transmit Sequence (PTS), Selective Mapping (SLM), Interleaved OFDM, Tone Injection (TI), Tone Reservation (TR), Active Constellation Shaping (ACS), Constrained Constellation Shaping (CCS) are some Multiple Signaling and Probabilistic techniques. Coding Techniques can be classified accordingly as Linear Block Coding, Golay sequences and Turbo codes [4].

Evolutionary Computational Techniques such as Genetic Algorithm (GA) [5, 6], Particle Swarm Optimization (PSO) [7,8], Cross Entropy (CE) [9], Electromagnetism like method (EM) [10], Artificial Bee Colony (ABC) , and Differential Evolution (DE) [11], Simulated Annealing (SA) [12] has been applied to the PTS technique in order to reduce PAPR further thereby providing less computational complexity.

Section II describes about the OFDM system and the cause of PAPR. Section III gives a brief note on PTS technique. Section IV briefs the Simulated Annealing PTS technique. Section V explains about the Particle Swarm Optimization technique. Section VI details the Scaled Offset PSO based PTS Technique. In Section VII, Simulation results and Discussion are provided. Concluding remarks are given in Section VIII.

II. OFDM and PAPR

The OFDM signal can be represented as

$$d(t) = \sum_{i=0}^{N-1} c_i e(j2\pi(f_c + k\Delta f)t) \quad (1)$$

$$= \exp(j2\pi f_c t)\sum_{i=0}^{N-1} c_i \exp(j2\pi k\Delta f t) \quad (2)$$

$$d(t) = \exp(j2\pi f_c t)c(t) \quad (3)$$

where $c_i, 0 \le i \le N-1$ are complex data and, $f_k = f_c + k\Delta f \;\; 0 \le k \le N-1$ is the k^{th} sub-carrier with f_c referring to the least sub-carrier frequency and Δf is the frequency spacing between the neighboring sub-carriers chosen to be $\frac{1}{T_S}$. This is to ensure that the sub-carriers are orthogonal to each other. If $c(t)$ is sampled at rate R samples/second where t is replaced by $\frac{nT_S}{N}$, $n = 0,1,2,...N-1$. $c(t)$ is expressed by the sampled function $c[n]$ can be expressed as

$$c[n] = \sum_{i-0}^{N-1} c_i \exp\left(j2\pi kn / N\right) \tag{4}$$

A. Peak to Average Power Ratio (PAPR)

PAPR is the ratio of the maximum instantaneous power to the average power of the signal. High PAPR can lead to various issues such as in-band distortion and out-of-band radiation [4].

$$PAPR = \frac{\max |x(t)|^2}{E|x(t)|^2} \tag{5}$$

Where $\max|x(t)|^2$ refers to the maximum instantaneous power and $E[.]$ refers to the expection operator.

B. Complementary Cumulative Distribution Function (CCDF)

One of the significant metrics used in evaluating PAPR is the Complementary Cumulative Distribution Function (CCDF). CCDF [4] can be defined as the probability that the PAPR of the n^{th} symbol greater than the threshold δ. CCDF can be expressed as

$$CCDF[PAPR(x^n(t))] = 1 - \left(1 - e^{-\delta}\right)^{\alpha N} \tag{6}$$

Where $PAPR\left(x^n(t)\right)$ refers to the PAPR of the n^{th} symbol and α refers to the oversampling factor.

III. PARTIAL TRANSMIT SEQUENCE (PTS) TECHNIQUE

The input data block is split into sub-blocks which are unequal in size represented by

$$X^{(k)}; k = 0,1,2,...K-1 \tag{7}$$

The summation of the sub-blocks can be represented as

$$X = \sum_{k=0}^{K-1} X^{(k)} \tag{8}$$

where $X^{(k)} = [X_0^{(k)} X_1^{(k)} ....X_{N-1}^{(k)}]$ and $X_i^{(k)} = X_k(or)0; 0 \le k \le K-1$. The sub-blocks are transformed as k time domain partial transmit sequences which can be given as

$$x^{(k)} = [x_0^{(k)} x_1^{(k)} ....x_{LN-1}^{(k)}] = IFFT_{LN \times N} X^{(k)} \tag{9}$$

The partial transmit sequences are multiplied with the phase factors where $b = b_k = e^{j\theta_k}; k = 0,1,2,...K-1$ and the signal with the least PAPR is selected for transmission. The main objective of PTS scheme is to combine the optimal phase factors such that the resultant signal has lowest PAPR. There are two drawbacks involved in PTS technique. One is its high computational complexity involved in selection of optimal phase factors and the other is the overhead that is involved in transmitting the side information from transmitter to the receiver side which also involves decoding operation.

The selection process of phase weighting factors can be optimized using meta-heuristic techniques such as Simulated Annealing, Particle Swarm Optimization.

IV. SIMULATED ANNEALING PTS TECHNIQUE

Simulated Annealing is based on the process of annealing of solid materials. Let s be the system state and $f(s)$ represents the energy of the system at a state s. The Track orientation from $s \longrightarrow \tilde{s}$ represents whether accepted or rejected based on Metropolis criteria. Assume $\Delta E = f(\tilde{s}) - f(s)$. If $\Delta E \prec 0$, track orientation $\tilde{s}$ is accepted. If $\Delta E \succ 0$, the track orientation $\tilde{s}$ is accepted when the acceptance probability ranges between 0 and 1. Simulated Annealing returns to the optimum when system is cooled down sufficiently or when the system reaches lowest energy. The value at which the system converges is known as global minimum. Some of the key parameters in SA are stopping criteria of annealing, Cooling Schedule and Transition Acceptance Probability. Stopping criteria may be either the number of iterations or once the system reaches the optimum value. Cooling schedule depends on the Initialization temperature T_0, Attenuation constant $T(i)$ here i refers to the number of iterations, stopping temperature T_f. Here T_0 should be large so that all transitions are accepted and $T(i)$ should be high so that the system is computationally efficient. The common cooling schedule that is used is given by (9)

$$T_1(i) = \alpha T_{i-1} \tag{10}$$

where α refers to the constant varying from $0.8 \prec \alpha \prec 1$.

The temperature at k^{th} descent can be given by

$$T_2(i) = T_0 \exp\left(-C\sqrt[D]{k}\right) \tag{11}$$

where D refers to the number of dimensional spaces in the model and C refers to the attenuation factor.

Acceptance probability is the probability that the new combination of phase factors that can be accepted when $\Delta E \succ 0$. The acceptance probability can be given by

$$Prob(i) = \left[1 - \frac{h.\Delta E}{T(i)}\right]^{\frac{1}{h}} \tag{12}$$

where h is a random real number that is not equal to 0 [12].

Some of the advantages in simulated annealing are its ability to approach global optima, flexibility, robust nature, versatility and the tuning nature, adaptability to deal with highly non-linear models, chaotic and noisy data [13].

Some of the drawbacks in SA are its trade-off between computational time and quality of answers obtained, Requirement of choices to turn into actual algorithm, Number precision in SA implementation has a significant effect upon quality of the solution obtained [13].

V. PARTICLE SWARM OPTIMIZATION BASED PTS TECHNIQUE

Particle Swarm Optimization (PSO) is a stochastic optimization technique based on the concept of bird flocking and fish schooling. The PSO technique mainly involves searching for an optimum solution in a swarm which consists of various particles. To obtain the optimum solution, the particles update their position and velocity based on local best and global best values.

The velocity and position of the particles are updated by the following equations

$$v_i(t+1) = \omega v_i(t) + c_1 r_1 \left(pbest(i,t) - p_i(t)\right) + c_2 r_2 \left(gbest(t) - p_i(t)\right) \tag{13}$$

$$p_i(t+1) = p_i(t) + v_i(t+1) \tag{14}$$

i -particle's index; N_P -total number of particles, t -current iteration number, f - fitness function, p -position, v -velocity, ω -inertia weight, r_1, r_2 -uniformly distributed random variables in the range [0,1], c_1, c_2 -acceleration constants [14].

Some of the notable features in PSO are its simple implementation, robustness to control parameters, higher computational efficiency when compared to the other techniques such as Genetic Algorithm, Simulated Annealing etc. Applications of PSO involve non-differentiable, non-linear, large search space problems and gives results with better efficiency. Some of the issues in the existing PSO technique are its low convergence rate in the iterative process, falls easily into the local optimum in high dimension space and suffers from partial optimism as well [15].

VI. SCALED OFFSET PARTICLE SWARM OPTIMIZATION BASED PTS (SOPSO-PTS)TECHNIQUE

The main focus of the Scaled Offset PSO-PTS scheme is to bring about a good PAPR reduction by the use of scaling constant and an offset value.

Step 1: Swarm Initialization

Initialize a swarm consisting of particles at random positions and velocities. Correlative Parameters such as Swarm size, Number of generations, Inertia weight, and Acceleration constants are initialized.

Step 2: Fitness function evaluation of particles

Fitness function or objective function of each individual particle is determined using the below formula

$$[b_1, b_2, ...b_k] = \underset{[b_1, b_2, ...b_k]}{\arg\min}\left(\max_{n=0,1,2,...N-1}\left|\sum_{k=1}^{K} b_k x_k[n]\right|\right) \tag{15}$$

Step 3: Comparing current objective value with local best and global best values

- Particle's objective function is compared with local best.
- If present value better than local best, local best=current value
- Next, Compare fitness function with global best value
- If current value better than global best, global best=current value.

Step 4: Updation of particle's velocity and position

The velocity and position of each particle is updated using the below expression

$$v_i(t+1) = \xi \omega v_i(t) + c_1 r_1 \left(pbest(i,t) - p_i(t)\right) + c_2 r_2 \left(gbest(t) - p_i(t)\right) + \zeta \tag{16}$$

$$p_i(t+1) = p_i(t) + v_i(t+1) \tag{17}$$

Where ξ refers to the scaling constant and ζ refers to the offset value.

By introducing the scaling factor in the first term, the inertia weight gets doubled which increases the particle's velocity. This in turn facilitates the global search and faster convergence of the swarm to the optimum value. The offset introduced as the fourth term helps in finding the solutions present in the unknown search space inside the swarm.

The scaling constant in the above equation has been dynamically varied from 0.5 to 4.5. PAPR performance is better for the value ξ = 2.0. There is no significant improvement in the PAPR performance for the scaling values greater than 2.0. The offset value ranges from 3.5 < ζ < 4.0

Step 5: Termination criterion

Until the desired condition (maximum number of iterations) is met, the steps are continued.

Figure 1 shows the block diagram of Scaled Offset PSO-PTS technique.

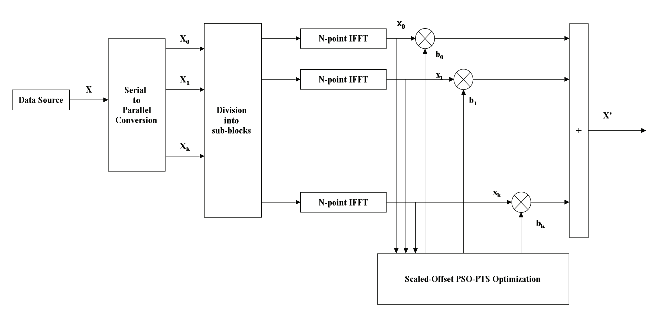

Fig 1. Block diagram of Scaled Offset PSO-PTS Technique

VII. Simulation Results and Discussion

Simulations were carried out using the MATLAB R2016a software. 16-QAM and 64-QAM modulation schemes were employed with 512 and 1024 sub-carriers. The CCDF at which PAPR is measured was 10^{-3}. The number of disjoint sub-blocks (M) is considered to be 4 and the phase weighting factors (W) are 4 which is given by $\{\pm 1, \pm j\}$.The type of partitioning involved in PTS is adjacent type. The swarm size and number of generations considered in PSO are 30 and 10 respectively. Inertia weight is considered to be 0.9. The acceleration constants c_1 and c_2 are considered to be 2.0 and 2.0 respectively. Table 1 shows the simulation parameters used for the proposed work.

TABLE I. Simulation Parameters

Modulation Scheme	16-QAM, 64-QAM
Number of sub-carriers (Nt)	512,1024
Number of sub-blocks (M)	4
Phase weighting factors (W)	4
Number of iterations(t)	3000
Swarm Size in PSO(N_P)	30
Generations in PSO (G)	10
Acceleration constants in PSO (c_1, c_2)	2.0, 2.0
Inertia Weight in PSO (ω)	0.9
Initialization temperature in SA (T_0)	1.0
Number of dimensional spaces in SA (D)	2
Attenuation factor in SA (C)	0.98

Figure 2 and Figure 3 depicts the simulation results of 16-QAM modulation scheme with 512 and 1024 subcarriers respectively.

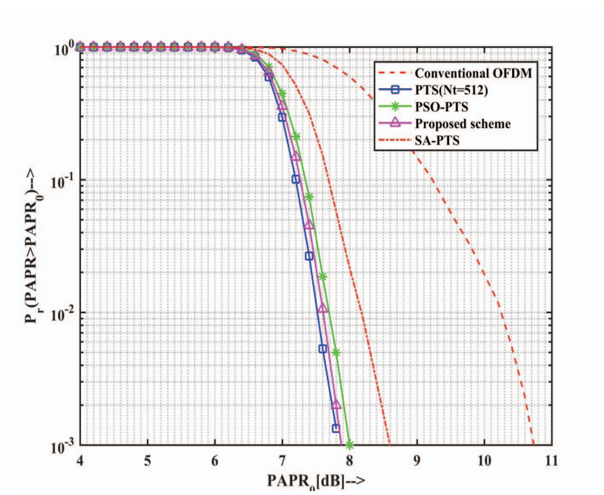

Fig 2. PAPR values of Conventional OFDM, PTS, SA-PTS and SOPSO-PTS for 16-QAM when Nt=512

Simulation results indicate that SOPSO-PTS scheme performs better in terms of PAPR reduction when compared to SA-PTS and PSO-PTS schemes. SOPSO-PTS has a better PAPR reduction of around 0.7 dB and 0.1 dB when compared to SA-PTS and PSO-PTS schemes respectively.

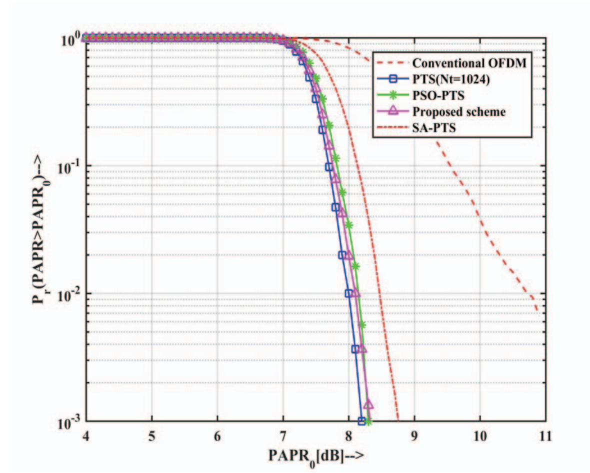

Fig. 3. PAPR values of Conventional OFDM, PTS, SA-PTS and SOPSO-PTS for 16-QAM when Nt=1024

Figure 4 and Figure 5 shows the simulated results of 64-QAM modulation scheme with 512 and 1024 sub-carriers respectively. At a CCDF value of10^{-3}, there is PAPR value of 7.9 dB in SOPSO-PTS scheme for Nt=512. For PSO-PTS schemes the PAPR values are 8.0 dB and 8.4 dB respectively in 512 sub-carriers and 1024 sub-carriers respectively. . For SA-PTS schemes, the PAPR values are 8.4 dB and 8.95 dB for Nt = 512, 1024 sub-carriers respectively. Therefore, SOPSO-PTS proves to be an efficient technique for PAPR reduction by outperforming both PSO-PTS and SA-PTS schemes.

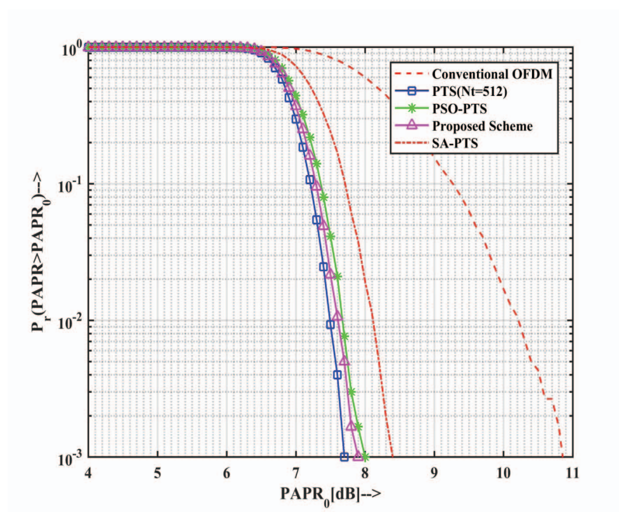

Fig. 4. PAPR values of Conventional OFDM, PTS, SA-PTS and SOPSO-PTS for 64-QAM when Nt=512

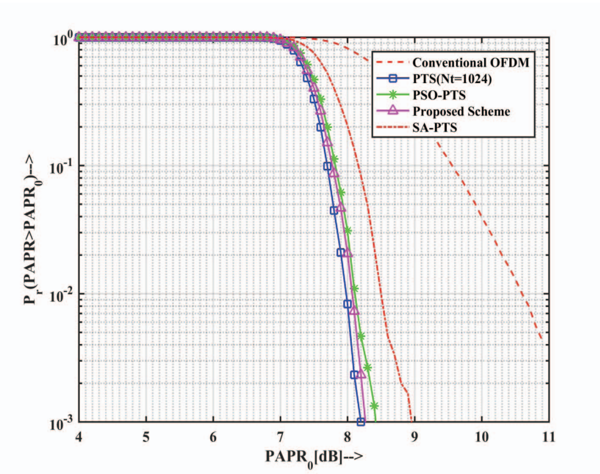

Fig. 5.PAPR values of Conventional OFDM, PTS, SA-PTS and SOPSO-PTS for 64-QAM when Nt=1024

VIII. CONCLUSION

A new improved scheme called Scaled Offset PSO based PTS for reducing PAPR in multi-carrier modulation systems has been proposed. The proposed scheme offers the advantages of faster convergence to the global optimum value and control mechanism is introduced to the particle's velocity by adding an offset value thereby reducing PAPR which makes it unique from other Conventional PSO schemes. When compared to the Conventional PTS, SA-PTS and PSO-PTS, Scaled Offset PSO-PTS proves to be an effective scheme in minimizing PAPR.

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