International Journal of Advanced Science and Technology
Vol. 29, No. 7s, (2020), pp. 5714-5724

GSA based PSO-PTS model for PAPR reduction in OFDM and MIMO-OFDM Systems

Sidramayya S M, Dr.K.Ramesha

Asst.Prof.Dept of ECE SGBIT,Belagavi, Bangalore.
Professor, Dept of ECE Dr.AIT,

siddu.matad@gmail.com, kramesha13@gmail.com

Abstract

Demand of wireless communication is increasing rapidly due to their significant use in daily life scenario. This increased demand has led towards the urge of efficient communication to meet the user requirements. Currently, Multiple Input Multiple Output - Orthogonal Frequency Division Multiplexing (MIMO-OFDM) has gained attraction from research community, and industries to improve the communication. The MIMO-OFDM technique helps to mitigate the interference among multiple users and improves the communication performance. However, during transmission, the power consumption remains a challenging task which increases Peak to Average Power Ratio (PAPR). This increment in PAPR reduces the communication quality. Several techniques have been reported recently but these techniques suffer from computational complexity and fail to achieve the desired performance. In order to overcome these issues, we present a novel hybrid optimization scheme by combining Particle Swarm Optimization (PSO) and Gravitational Search Algorithm (GSA). The PSO scheme helps to achieve the optimal solution and GSA helps to minimize the search operation using local search mechanism. We have conducted an experimental study which shows a significant improvement in PAPR reduction. Moreover, a comparative study is also presented which shows that proposed approach achieves better performance when compared with existing techniques of PAPR reduction in MIMO-OFDM systems.

Keywords – GSA, PSO-PTS , MIMO,OFDM , PSO, PAPR.

I. INTRODUCTION

Demand of wireless cellular communication has increased drastically during last decade. In order to meet the communication quality standards, OFDM is considered as a promising technique. Generally, the OFDM systems have significant nature to deal with multipath fading hence these systems are widely adopted in various OFDM standards such as 3GPP, Long Term Evolution (LTE), and LTE-Advanced etc... [1]. Moreover, the OFDM technology has several benefits such as high spectral efficiency, high speed data rate, frequency selective fading, and robustness against narrow band interference [2]. OFDM mitigates the Inter Symbol Interference (ISI) with the help of Guard Interval (GI), Cyclic Prefix (CP), and frequency selectivity of multi-path channel. Due to this, the hardware implementation of OFDM systems become cheaper, and simple solution for communication systems.

Currently, the OFDM technology is widely adopted in various real-time communication standards such as Digital Video Broadcasting (DVB), Digital Audio Broadcasting (DAB), Digital Subscriber Lines (DSL), Wireless Metropolitan Area Networks (WMAN), Wireless Local Area Networks (WLAN), Wireless Personal Area Networks (WPAN) and Wireless Area Networks (WAN) etc. Along with this, the OFDM systems are proposed in various wireless communication standards such as IEEE 802.11, IEEE 802.16, and IEEE 802.15.3a.

Despite of several advantages of OFDM, these systems suffer from PAPR related issues which has significant impact on the transmitted signal and system performance. In order to generate the zero-distortion in the signal, the High-Power Amplifier (HPA) must operate in linear region hence, RF HPA require high dynamic range for OFDM systems. These amplifiers are very expensive and creates implementation cost as a challenging issue for OFDM systems. Hence, reducing the PAPR helps to reduce the complexity of Analogue to Digital (A/D) and Digital to Analogue (D/A) convertors, and improving the Signal to Noise Ratio (SNR). During last decade, several techniques have been introduced to overcome the PAPR reduction relation such as coding schemes [3], constellation shaping [4], non-linear companding transform [5], phase, optimization [6], Partial Transmit Sequence (PTS) [7], precoding based selected mapping [8], tone reservation [9], tone injection [10], clipping & filtering, precoding [11] and selected mapping [12] are the widely adopted techniques for PAPR reduction. According to these techniques, selection of optimal parameter to reduce the PAPR is tedious task because of long process for parameter selection. Hence, optimization schemes are introduced in this field of research where different types of optimization techniques are incorporated to obtain the optimal solution for PAPR reduction such as iterative clipping and filtering optimization [13], PSO based PTS optimization [14], harmony search optimization [15], firefly optimization [16], cuckoo search optimization [17] and many more. Similarly, genetic algorithm, artificial bee colony, and other machine learning approaches are also studied and implemented to obtain the reduced PAPR [18]. However, recent studies have revealed that the existing techniques suffer from various challenges where finding the optimal solution in minimum search is considered as a tedious task. Hence, PSO based PTS technique is widely adopted due to its significant performance. Several techniques are presented based on the particle swarm optimization. However, reducing the search operation remains a hot research topic to improve the performance. Hence, in this work, we focus on optimizing the PSO to reduce the search operation for better performance.

The main contribution of the work includes development of a novel combined approach to overcome the optimization related issues in OFDM for PAPR reduction. In order to develop this scheme, we consider GSA and PSO schemes where GSA is used for local search and PSO helps to obtain the global best solution hence the search complexity is reduced. The rest of the article is organized as follows: section II presents the literature review about recent techniques of PAPR reduction using different optimization techniques, section III presents the proposed solution using hybrid GSO-PSO based PTS scheme, section IV presents comparative experimental study using proposed approach and finally, section V presents concluding remarks and future work direction in this field.

II. LITERATURE SURVEY

In this section, we present a brief discussion about recent techniques of PAPR reduction in MIMO-OFDM systems. Generally, PTS and (Selective Mapping) SLM are the widely known techniques for PAPR reduction. Several approaches have been presented based on these techniques such as Ku et al., [19] presented reduced complexity PTS based PAPR reduction technique and presented a selection method to select time-domain samples. This study reported a low-complexity PTS model. Based on these assumptions, Lee et al., [20] presented low-complexity PTS technique for OFDM systems. This study introduces a new model to select the time-domain samples. In order to select the optimal samples, the rotating samples of the each subblock is obtained with the help of inverse FFT. With the help of the time-domain samples, the pre-exclusion is obtained to obtain the reduced computational complexity. Recently, researchers have focused on optimizing the performance of PTS based PAPR reduction and introduced several approaches optimization techniques such as particle swarm optimization, genetic algorithm, grey-wolf optimization, simulated annealing and various search optimization algorithms etc.

Joshi et al., [21] reported that PTS is considered as a promising technique which has significant impact on the performance of OFDM systems. The main aim of this approach to find the optimal phase to generate the lowest PAPR as system outcome. The updated information about updated phase set about transmitter is forwarded to the receiver as side information. This information is used later to decode the data. Moreover, the side information consumes extra bandwidth which reduces overall bandwidth efficiency. Hence, to overcome these issues, authors introduced genetic algorithm-based PTS approach. This approach doesn't require any side information and uses low-complex receivers; hence it helps to improve the network performance. Moreover, genetic algorithm helps to reduce the searches to find the optimal solution for phase searches resulting in low computations. Sharif et al., [22] also reported that the PTS is considered efficient approach to reduce the PAPR but conventional PTS techniques suffer from the phase rotation factors and computational complexity related issues. Hence, authors introduced a hybrid genetic algorithm (GA) based approach to select the salient phase factors using iterative optimization model. According to this approach, a new local search optimization is applied and optimum phase factor search is also incorporated to reduce the complexities. The main contribution of this model is to represent the chromosome for modified crossover operation. Similarly, Hassan et al.,[23] focused on GA based approach and incorporated fuzzy logic model to improve the system performance where 49 fuzzy rules are constructed to reduce the complexity.

Recently, swarm optimization-based schemes are also adopted widely to reduce the PAPR in OFDM systems. Aghdam et al., [14] presented particle swarm optimization (PSO) based scheme to reduce the PAPR by selecting the optimal phase rotations. Lahcen et al., [24] introduced Fireworks Algorithm (FWA) to improve the performance of PTS based PAPR reduction. Similar to this, Amhaimar et al., [27] presented improved FWA approach to reduce the PAPR ad incorporated PTS. Kumar et al., [25] presented a novel combined optimization approach using a combination of Particle Swarm Optimization (PSO) and Grey Wolf Optimizer (GWO). Similar to this approach, Rao et al.,[26] also focused on PAPR reduction and presented a combination of PTS approach with meta-heuristic optimization model. In this work also, authors combined PSO and Grey Wolf Optimizer (GWO). Tan et al., [28] focused on the Artificial Bee Colony (ABC) approach and presented an improved model of ABC in the combination with PTS to achieve the reduced PAPR. In [29], authors presented EABC-PTS enhanced ABC model with PTS for Space Time Block Code (STBC) systems. Initially, authors present orthogonal initialization model to generate the initial population further, the complexity issues are addressed using suboptimal solution for optimal phase selection. Similarly, SLM based techniques are also adopted for PAPR reduction along with optimization strategies. Mestdagh et al., [12] introduced selective mapping-based approach for PAPR reduction in MIMO OFDM systems. According to this approach, the SLM-OFDM based model generates $\left(\frac{U^2}{4}\right)$ symbols using inverse fast Fourier transform, Sudha et al., [30] introduced low complexity PAPR reduction in SLM-OFDM with the help of domain-sequence separation model. In order to achieve this, the outcome of Inverse Fat Fourier Transformer (IFFT) is partitioned as real odd, real even, imaginary odd and imaginary even using Fourier transform. Later, the real values are considered for transforming into imaginary sequence whereas imaginary data is shifted into time-reversal shifted sequence.

Tang et al., [31] discussed about iterative clipping and filtering techniques for PAPR reduction. According to this work, authors introduced optimized ICF (OICF), and simplified OICF (SOICF) to achieve the faster convergence and solving the convex optimization problems. Later, clipping-noise compression (CNC) method is applied to reduce the computational complexities. Miao et al., [8] presented multi-band (MB)-Hadamard precoding and clipping to reduce the PAPR for OFDM systems. In this model, signal to noise ratio of is measured for the entire transmission link for clipping and quantization noise.

III. PROPOSED MODEL

In this section we present the proposed solution to reduce the PAPR for OFDM systems. First of all, we describe the PAPR and PTS based approach to minimize the PAPR. Later, conventional PSO and improved PSO models are presented to improve the PAPR performance.

3.1 Peak-To-Average Power Ratio

The OFDM systems play important role in wireless cellular communication by improving the system throughput and reliability. Generally, these models generate huge number of symbols during transmission which consume more power resulting in increased PAPR. According to section 1, the PAPR is considered the challenging task and section 2 described several techniques for PAPR reduction. In section 2, we have concluded that PTS is the most effective and widely adopted solution for PAPR related issues such as identification of optimal phase factors. Hence, in this subsection, we present the PAPR modeling.

Let us consider that the data block length is N is represented in vector form as $\boldsymbol{X} = [X_0, X_1, \dots . X_{N-1}]^T$ **.** Each symbol in the data vector $\boldsymbol{X}$ modulates one of the set of subcarrier, denoted as $\{f_n, n = 0,1, \dots N-1\}$. The subcarrier is considered as orthogonal and represented as $f_n = n\Delta f$ where Δf is denoted $\Delta f = \frac{1}{NT}$ and NT is the duration of OFDM data block $\boldsymbol{X}$**.** With the help of these assumption, the transmitted OFDM signal can be expressed as:

$$x(t) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} X_n e^{j2\pi f_n t} \ , 0 \le t < NT \tag{1}$$

Hence, the PAPR of the given signal can be expressed as:

$$PAPR = \frac{\max\limits_{0 \le t < NT} |x(t)|^2}{\frac{1}{NT} \cdot \int_0^{NT} |x(t)|^2 dt} \tag{2}$$

At this stage, the main aim of PAPR reduction techniques is to minimize the $\max\big(x(t)\big)$, however, most of the existing models utilize discrete-time signals and amplitude of discrete-time signals is considered in PAPR reduction techniques. Generally, this data is sampled based on the symbol spaces and misses some peaks which affects the PAPR performance, hence, signal oversampling is applied with the factor of L to approximate the actual PAPR. The oversampled time-domain samples can be obtained using inverse discrete Fourier transform (IDFT) along with $(L-1)N$ zero padding. This can be expressed as:

$$PAPR = \frac{\max\limits_{0 \le t < NL-1} |x(t)|^2}{E\ \lfloor x_t \rfloor^2} \tag{3}$$

Where $E[.]$ Denotes the expected value

3.2 PAPR reduction using PTS technique in OFDM systems

In this section, we present the modelling of PTS technique to reduce the PAPR for OFDM systems. According to PTS scheme, each input data block is partitioned into different subblocks and each subblock is multiplied by a phase weighting factor. Below given figure 1 shows the block diagram of PTS technique.

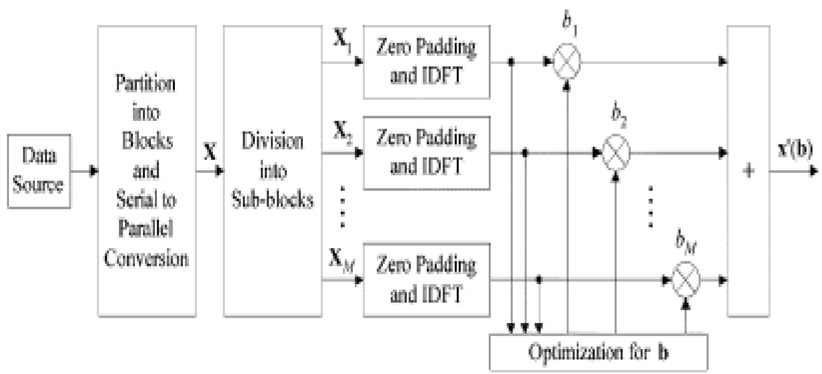

Fig.1. PAPR Reduction using PTS

The phase weighting plays important role to reduce the PAPR. We consider a data block $\boldsymbol{X}$ as mentioned in previous section and the data block is divided into M disjoint blocks as:

$$\boldsymbol{X} = \sum_{i=1}^{M} \boldsymbol{X}_i \tag{4}$$

It is assumed that $\boldsymbol{X}_i$ is a cluster which contains a set of multiple subblocks of equal size. Here, the goal of PTS model is to generate a weighted combination of M sub-blocks which can be expressed as:

$$\boldsymbol{X}' = \sum_{i=1}^{M} W_i \boldsymbol{X}_i \text{ and } W_i = e^{j\phi_i} \tag{5}$$

Where $W_i, i = 1,2, \dots. M$. in this approach, the phase weighting factor can be selected any value in the range of $[0,2\,\pi)$. As discussed before, the selection of phase weighting vector is a tedious task which hence finite number of elements are selected to reduce the search complexity. After applying the transform domain, the newly obtained time-domain signal can be expressed as:

$$\boldsymbol{x} = IFFT\left\{\sum_{\boldsymbol{i=1}}^{\boldsymbol{M}} W_i.\boldsymbol{X_i}\right\} = \sum_{\boldsymbol{i=1}}^{\boldsymbol{M}} W_i\, IFFT\{X_i\} \tag{6}$$

Finally, the obtained partial sequences can be rotated with the help of a phase weight factor W_i. However, the optimal phase weighting factor can be selected using all possible 2^{M-1} combinations. The main aim of PTS is to identify the phase weighting vector as $\boldsymbol{W} = \{W_1, W_2, ..W_i\}$ which can reduce the PAPR of $\boldsymbol{X}'$. Obtaining optimal parameters from given OFDM symbol can be expressed as:

$$\widehat{\boldsymbol{W}} = \arg\min_{w}\left\{\max\left|\sum_{i=1}^{M} W_i, \boldsymbol{X}_i\right|\right\} \tag{7}$$

According to figure 1, we need to obtain the optimization parameters to reduce the PAPR. In order to do this, several optimization techniques have been discussed as mentioned previous section where combination of PTS and PSO outperformance when compared with conventional optimization-based PTS algorithms.

3.3 PSO based PTS for PAPR reduction

Particle swarm optimization techniques has been adopted widely for PAPR reduction. In this section, we present a PSO based PTS technique to reduce the PAPR in OFDM systems. the main aim of optimization techniques is to obtain the optimal solution for block b as given in figure 1. In order to achieve this, PSO technique is implemented where initial population is called as swarm and individuals are denoted as particles. According to a social behavior, the swarm of bees try to find the most flowers in the field. The optimization process depends on the population of particles which fly in the considered space with a dynamically adjusted velocity and position. These positions are adjusted according to their flying experience and best solutions are obtained. According to PSO-PTS mode, the potential solutions is presented in the vector form as x where weighting factor is denoted by W and moving velocity of particles is dented as v. The velocity and position for i^{th} particle of any $K-$dimensional optimization problem can be represented as $V_i = (v_{i,1}, v_{i,2}, \dots v_{i,K})$ and $\boldsymbol{W}_i = (w_{i,1}, w_{i,2}, \dots w_{i,K})$. Each particle has the best position which is referred as est , it is known as local best solution and denoted as $W_i^P = (W_{i,1}, W_{i,2}, \dots W_{i,K})$. The $pbest$ denotes best objective value so far at time t. Similarly, the global best $(gbest)$ is denoted as $W^G = (W_{i,1}, W_{i,2}, \dots W_{i,K})$ which shows the current global best solution for entire optimization problem for the considered swarm. The new velocity of swarm can be expressed as:

$$v_i(t+1) = wv_i(t) + c_1r_1\left(W_i^P(t) - W_i(t)\right) + \ c_22\left(W_i^G(t) - W_i(t)\right) \tag{8}$$

Where $v_i(t)$ denotes the old-velocity of i^{th} particle at time t , c_1 and c_2 denotes cognitive and social rates which are used for obtaining the global and local best solutions and helps to balance the global and local best solution, w is an inertia weight which is used to modify the previous velocity related history to obtain the next best solution and . r_1 and r_2 are the two random values which provide uniform distribution in the range of [0,1]. With the help of new velocities, the updated positions can be expressed as:

$$W_i(t+1) = W_i(t) + v_i(t+1) \tag{9}$$

In this stage, the particles move towards the new position and fitness of each solution is computed and new population is generated.

3.4 Proposed Improved PSO model for PAPR reduction

Previous section presents the optimization problem to minimize the PAPR to improve the OFDM performance. The existing PSO based PTS approaches fails to achieve the optimal number of solutions in minimum search operations which generates poor PAPR performance. To overcome the PAPR related issue, we present PSO based optimization strategy which minimized the PAPR with reduced search operations with low computational complexity. In order to improve the performance, we incorporate the gravitational search optimization algorithm in PSO based PTS scheme for PAPR reduction.

The gravitational search algorithm is based on the Newton's theory which states that each particle attracts other particle with a force. The attraction force is inversely proportional to the square of the distance and directly proportional to the product of the particle mass. In GSA we consider that the masses of particles are directly proportional to the fitness value. Because, heavier mass will have more attraction force and it becomes easy to obtain the global optimal solution. In GSA, we consider N number of agents which are deployed randomly in the given subspace. During this process, the gravitational force by agent j on agent i on time t is given as:

$$F_{ij}^d(t) = \left(x_j^d(t) - x_i^d(t)\right) \times \frac{M_{pi}(t) \times M_{aj}(t)}{R_{ij}(t) + \varepsilon} \times G(t) \tag{10}$$

$M_{aj}(t)$ denotes the active gravitational force of j, M_{pi} denotes the passive gravitational force of agent i, $G(t)$ gravitational constant at time t, R_{ij} is the Euclidean distance between agent i and j, and ε is a small constant. The gravitational $G(t)$can be computed as:

$$G(t) = G_0 \times \exp\left(-\alpha \times \frac{iter}{maxiter}\right) \tag{11}$$

α is descending coefficient and G_0 is the initial value, $iter$ denotes current iterations and $maxiter$ denotes maximum number of iterations. Similarly, the total force on the agent i can be computed as:

$$F_i^d(t) = \sum_{j=1, j\neq i}^{N} r\, F_{ij}^d(t) \tag{12}$$

Where r is the random number which is uniformly distributed in the range $[0,1]$.

Further, we measure the acceleration of agent which is based on the force and mass. This can be computed as:

$$ac_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)} \tag{13}$$

Where t denotes the time and M_i denotes the mass of i^{th} agent. Thus, the updated velocity and positions of agents can be computed as:

$$\begin{aligned} v_i^d(t+1) &= r_i \times v_i^d(t) + ac_i^d(t) \\ x_i^d(t+1) &= x_i^d(t) + v_i^d(t+1) \end{aligned} \tag{14}$$

In order to improve the search operations, we incorporate gravitational search optimization with particle swarm optimization which provides the optimal solution for optimization block b as given in figure 1. This combination helps to achieve the best solution for $gbest$ with the help of local search operations of GSA. The updated velocity using PSO and GSA can be given as:

$$V_i(t+1) = V_i(t) \times w + r_1 \times c_1' \times ac_i(t) + c_2' \times r_1 \times \left(gbest - X_i(t)\right) \tag{15}$$

V_i is the velocity of agent i, w is the weighting factor, r_1 random number and $ac_i(t)$ is the acceleration for agent i . Similarly, the particle positions can be updated as:

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{16}$$

According to the proposed combined approach, initially, all agents are initialized randomly and each agent is considered as candidate solution. In the next phase, the gravitational phase, gravitational constant, and other forces are computed and finally the acceleration parameter is computed. After computing the acceleration, the best solution must be updated in every iteration. This process is repeated until the optimal solution are obtained. The main advantage of proposed approach is that it uses GSA as local search which reduces number of searches and provides optimal solution faster.

IV. RESULTS AND DISCUSSION

In this section, we present the comparative performance in terms of PAPR reduction for OFDM system. According to proposed approach, we have considered partial transmit sequence PAPR reduction as our base model and incorporated improved particle swarm optimization (PSO) based scheme to improve the system performance. The simulation study is conducted using IEEE 802.16e (WiMAX) communication standards. The IEEE 802.16e standard considers 256 subcarriers, where total data is carried by 192 subcarriers where 8 subcarriers are used as pilot for channel estimation. Table 1 shows the complete simulation parameters considered for this comparative analysis.

Table 1. Simulation Parameters

Parameters	Considered Values
FFT size	256
Subcarrier	192
Pilot carrier	8
Guard Band Subcarrier	56
Modulation	QPSK
Number of subblocks	$V = 2,4,6,8$
Channel Type	AWGN
Channel Bandwidth	3.5 MHz

According to this experiment, initially, we generate total 10^4 random symbols for transmission using OFDM standards. On this data, we apply QPSK modulation using oversampling factor as 4 and the modulated data is transmitted over AWGN channel.

The performance of proposed approach is compared with existing optimization techniques such as fireworks algorithm (FWA) [24], standard particle swarm optimization (SPSO) [32], partial transmit sequence (PTS) [33], genetic algorithm (GA) [24], simulated annealing (SA) [4], and SLM methods [34] in terms of PAPR reduction. Figure 1 shows a comparative performance in terms of PAPR reduction performance where we have considered different types of optimization algorithms.

According to figure 1, we have compared the performance of proposed approach with state-of-art techniques. This experiment shows that we have obtained PAPR reduction performance as 13.5 dB, 10.22 dB, 7.8 dB, 7.1 dB, 7.1dB 6.2 dB, 4.1 dB,3.2 dB using Original OFDM, SLM, GA-PTS, PTS based SA, PTS based SPSO, conventional PTS, PTS based FWA, and proposed hybrid PSO, respectively.

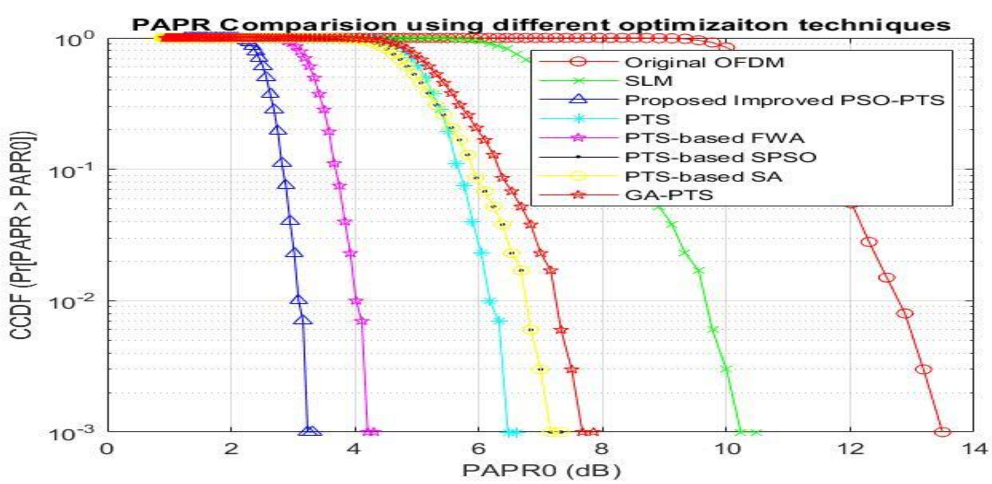

Fig.1. PAPR Comparison using Different Techniques.

Similarly, we compare the performance of proposed approach for varied number of transmitter antennas. The obtained performance is depicted in figure 2.

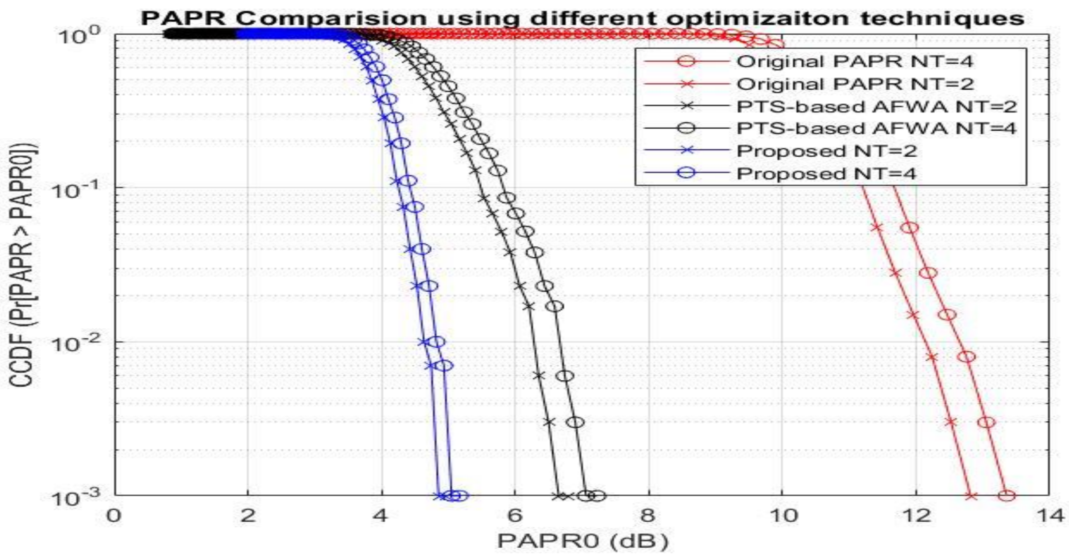

Fig.2. PAPR Comparison for Varied Number of Transmitter Antennas

According to this experiment for varied number of antennas as 2 and 4 for original OFDM, PTS based AFWA and proposed model. Each experiment shows that, more number of antennas achieves more PAPR. The proposed approach achieves better performance as 4.5 dB and 4.8 dB for 2 and 4 transmitter antennas, respectively.

CONCLUSION

In this work we have focused on the MIMO-OFDM system and presented a novel approach to improve the communication performance. Generally, these systems suffer form high power consumption performance during data transmission which increases the peak average to power ratio (PAPR) during communication. In this work, we have presented a novel hybrid approach to reduce the PAPR. According to this work, we have presented Particle swarm optimization scheme to obtain the optimal solution and gravitational search algorithm (GSA) is applied to minimize the local search operation to reduce the computational complexity. These schemes are incorporated in PTS scheme of PAPR reduction. Proposed approach shows a significant improvement in the PAPR reduction.

REFERENCES

1. Wang, S. H., Li, C. P., Lee, K. C., & Su, H. J. (2015). A novel low-complexity precoded OFDM system with reduced PAPR. IEEE Transactions on Signal Processing, 63(6), 1366-1376.
2. Almoneer, M., Rohde, C., Hassan, K., & Gerstacker, W. H. (2017). Intercarrier interference-aware pilot-aided channel estimation in OFDM systems. IEEE Transactions on Broadcasting, 63(3), 449-462.
3. Jiang, T., & Wu, Y. (2008). An overview: Peak-to-average power ratio reduction techniques for OFDM signals. IEEE Transactions on broadcasting, 54(2), 257-268.
4. Kakkavas, A., Xu, W., Luo, J., Castaneda, M., & Nossek, J. A. (2017, July). On PAPR characteristics of DFT-s-OFDM with geometric and probabilistic constellation shaping. In 2017 IEEE 18th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC) (pp. 1-5). IEEE.

5. Xin, D., Xu, Q., Qiao, S., & Zhang, T. (2019). Non-linear companding transform for DCO-OFDM-based VLC systems. IET Communications, 13(8), 1110-1114.
6. Ali, T. H., & Hamza, A. (2016). A new SLM technique based on Genetic Algorithms for PAPR reduction in OFDM systems. International Journal of communications, 10, 91-94.
7. Prasad, S., & Jayabalan, R. (2019). PAPR reduction in OFDM using scaled particle swarm optimisation based partial transmit sequence technique. The Journal of Engineering, 2019(5), 3460-3468.
8. Miao, P., Chen, P., & Chen, Z. (2018). Low-complexity PAPR reduction scheme combining multi-band Hadamard precoding and clipping in OFDM-based optical communications. Electronics, 7(2), 11.
9. Bulusu, S. K. C., Crussière, M., Hélard, J. F., Mounzer, R., Nasser, Y., Rousset, O., & Untersee, A. (2018). Quasi-optimal tone reservation PAPR reduction algorithm for next generation broadcasting systems: A performance/complexity/latency tradeoff with testbed implementation. IEEE Transactions on Broadcasting, 64(4), 883-899.
10. Wang, W., Hu, M., Li, Y., & Zhang, H. (2016). A low-complexity tone injection scheme based on distortion signals for PAPR reduction in OFDM systems. IEEE Transactions on Broadcasting, 62(4), 948-956.
11. Anoh, K., Tanriover, C., Adebisi, B., & Hammoudeh, M. (2017). A new approach to iterative clipping and filtering PAPR reduction scheme for OFDM systems. IEEE Access, 6, 17533-17544.
12. Mestdagh, D. J. G., Monsalve, J. G., & Brossier, J. M. (2018). GreenOFDM: a new selected mapping method for OFDM PAPR reduction. Electronics Letters, 54(7), 449-450.
13. Anoh, K., Tanriover, C., & Adebisi, B. (2017). On the optimization of iterative clipping and filtering for PAPR reduction in OFDM systems. IEEE Access, 5, 12004-12013.
14. Aghdam, M. H., & Sharifi, A. A. (2019). PAPR reduction in OFDM systems: An efficient PTS approach based on particle swarm optimization. ICT Express, 5(3), 178-181.
15. Singh, M., & Patra, S. K. (2017). Partial transmit sequence optimization using improved harmony search algorithm for PAPR reduction in OFDM. ETRI Journal, 39(6), 782-793.
16. Singh, M., & Patra, S. K. (2018). On the PTS Optimization Using the Firefly Algorithm for PAPR Reduction in OFDM Systems. IETE Technical Review, 35(5), 441-455.
17. Yan, Y., & Pingping, X. (2017, October). PAPR reduction of FBMC-OQAM signals based on cuckoo search optimization algorithm. In 2017 IEEE International Conference on Signal Processing, Communications and Computing (ICSPCC) (pp. 1-5). IEEE.
18. Joshi, A., Garg, A., Garg, E., & Garg, N. (2019). PAPR Reduction Analysis of OFDM Systems Using GA-, PSO-, and ABC-Based PTS Techniques. In Advances in Signal Processing and Communication (pp. 145-155). Springer, Singapore.
19. Ku, S.-J., Wang, C.-L., Chen, C.-H.: 'A reduced-complexity PTS-based PAPR reduction scheme for OFDM systems', IEEE Trans. Wirel. Commun., 2010, 9, (8), pp. 2455–2460
20. Lee, K.-S., Woo, J.-Y., Shin, D.-J., Cho, Y.-J., & No, J.-S. (2016). Low-complexity PTS schemes using OFDM signal rotation and pre-exclusion of phase rotating vectors. IET Communications, 10(5), 540–547. doi:10.1049/iet-com.2015.0192
21. Joshi, A., & Saini, D. S. (2017). GA-PTS using novel mapping scheme for PAPR reduction of OFDM signals without SI. Wireless Personal Communications, 92(2), 639-651.
22. Sharif, A. A., & Aghdam, M. H. (2019). A novel hybrid genetic algorithm to reduce the peak-to-average power ratio of OFDM signals. Computers & Electrical Engineering, 80, 106498.
23. Hassan, Z. A., & Hasan, A. A. (2019, April). Genetic-fuzzy algorithm based suboptimum partial transmit sequences scheme for peak-to-average power ratio reduction in MIMO-OFDM systems. In Proceedings of the International Conference on Information and Communication Technology (pp. 74-80). ACM.

24. Lahcen, A., Mustapha, H., Ali, E., Saida, A., & Adel, A. (2019). Peak-to-Average Power Ratio Reduction Using New Swarm Intelligence Algorithm in OFDM Systems. Procedia Manufacturing, 32, 831-839
25. Kumar, P. R., Naganjaneyulu, P. V., & Prasad, K. S. (2019). Hybrid PS–GW optimised PTS scheme for PAPR reduction in OFDM system. IET Communications, 13(18), 2996-3002.
26. Rao, R. S., & Malathi, P. (2019). A novel PTS: grey wolf optimizer-based PAPR reduction technique in OFDM scheme for high-speed wireless applications. Soft Computing, 23(8), 2701-2712.
27. Amhaimar, L., Ahyoud, S., Elyaakoubi, A., Kaabal, A., Attari, K., & Asselman, A. (2018). PAPR Reduction Using Fireworks Search Optimization Algorithm in MIMO-OFDM Systems. Journal of Electrical and Computer Engineering, 2018.
28. Tan, X., Wang, H., & Dai, X. (2019). A PAPR Reduction Method Based on Modified Artificial Bee Colony Algorithm for OFDM Signals (No. 836). EasyChair.
29. Kumutha, D., & Prabha, N. A. (2017). Hybrid STBC-PTS with enhanced artificial bee colony algorithm for PAPR reduction in MIMO-OFDM system. Journal of Ambient Intelligence and Humanized Computing, 1-17.
30. Sudha, V., & Kumar, D. S. (2018). Low complexity PAPR reduction in SLM-OFDM system using time domain sequence separation. Alexandria engineering journal, 57(4), 3111-3115.
31. Tang, B., Qin, K., Mei, H., & Chen, C. (2019). Iterative Clipping-Noise Compression Scheme for PAPR Reduction in OFDM Systems. IEEE Access, 7, 134348-134359
32. D. Bratton and J. Kennedy, “Defining a standard for particle swarm optimization,” in Proceedings of IEEE Swarm Intelligence Symposium (SIS), pp. 120–127, Honolulu, HI, USA, April 2007
33. Cai, B., Liu, A., & Liang, X. (2019). Low-Complexity Partial Transmit Sequence Methods Using Dominant Time-Domain Samples for Multicarrier Faster-Than-Nyquist Signaling. IEEE Access, 7, 121552-121564
34. Tören, M., & Çiflikli, C. (2018). Peak-to-Average-Power-Ratio (PAPR) reduction Methods with wavelet transform in MIMO-OFDM. *IETE Journal of Research*, *64*(3), 415-421.