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PSO-DBNet for Peak-to-Average Power Ratio Reduction Using Deep Belief Network

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Abstract: Data transmission through a wireless network has faced various signal problems in the past decades. The orthogonal frequency division multiplexing (OFDM) technique is widely accepted in multiple data transfer patterns at various frequency bands. A recent wireless communication network uses OFDM in long-term evolution (LTE) and 5G, among others. The main problem faced by 5G wireless OFDM is distortion of transmission signals in the network. This transmission loss is called peak-to-average power ratio (PAPR). This wireless signal distortion can be reduced using various techniques. This study uses machine learning-based algorithm to solve the problem of PAPR in 5G wireless communication. Partial transmit sequence (PTS) helps in the fast transfer of data in wireless LTE. PTS is merged with deep belief neural network (DBNet) for the efficient processing of signals in wireless 5G networks. Result indicates that the proposed system outperforms other existing techniques. Therefore, PAPR reduction in OFDM by DBNet is optimized with the help of an evolutionary algorithm called particle swarm optimization. Hence, the specified design supports in improving the proposed PAPR reduction architecture.

Keywords: 5G; wireless network; orthogonal frequency division multiplexing; signal distortion; peak to average power ratio; partial transmit sequence; deep belief network

1 Introduction

Advanced wireless communication network, such as long-term evolution (LTE), advanced LTE, and others (including 802.11), uses orthogonal frequency division multiplexing (OFDM). The important reason behind this technological usage is it provides robust multipath propagation technology with minimal complex design on transceiver. Nevertheless, the advantage system affects by high peak-to-average power ratio (PAPR). This loss is mainly caused by signal distortion during transmission using nonlinear amplifiers. Therefore, the majority of researchers are interested in reducing PAPR of OFDM in a wireless communication system. This investigation and reduction are beneficial for future generation networks of 5G/6G in improving communication systems [1–4]. Numerous methods, such as clipping scheme, partial transmission scheme, and selective mapping, are used in the reduction of PAPR. The clipping scheme uses a deliberate power amplifier that results in minimal PAPR but also increases the bit error rate (BER) in the signal transmission. Another implemented scheme is called signal scrambling, in which the phase factor of the scrambled signal is required for the receiver to reconstruct missed signals in the transmission. The process of finding the phase factor is an extremely complex task.

Recently, artificial intelligent techniques are used in the reduction of PAPR. Deep learning-based multiple layers of perceptron is used to connect the input to the output layers as neurons that behave in the human brain. These techniques provide high performance when compared with some of the traditional schemes. Various applications, such as image processing and recognition, use deep learning as the potential algorithm for highly complex systems [5,6]. Channel encoding and decoding [7] is a deep learning that provides better results than conventional outcomes. Convolutional neural network [8] was used for radio modulation variation recognition. On the basis of the preceding scenario, deep learning is highly fit to solve the problem of PAPR in the proposed methodology. The main contributions of this research is as follows:

- We reduce PAPR in OFDM using deep belief neural network (DBNet), which has been optimized with the evolutionary algorithm called particle swarm optimization (PSO). This design helps improve the proposed PAPR reduction architecture.
- Partial transmit sequence (PTS) is merged with the proposed DBNet model. This sequence helps to check transit signals without distortion during the transmission process.
- Distortion is measured clearly and deep learning detects accurately, thereby helping in the reduction of PAPR in OFDM.

The remainder of this paper is organized as follows. Section 2 presents the existing research on the concept of PAPR reduction. Section 3 discusses the proposed architecture and algorithm. Section 4 implements the proposed model and evaluates the result with various traditional schemes. Section 5 concludes the proposed research with its future scope.

2 Related Research

Rahmatallah et al. [9] surveyed the peak-to-average ratio reduction in OFDM with the impact of power amplifiers, thereby causing non-linear distortion. Their survey also evaluated the performance of the PAPR reduction methods. These methods were classified based on signal distortion, coding approaches, and multiple signaling. Similarly, the complexity of the PAPR schemes was analyzed.

Han et al. [10] proposed an overview of the PAPR reduction schemes for multicarrier transmission, such as clipping, filtering, coding, partial transmit sequence, interleaving, tone reservation, selected mapping, and active constellation extension. In addition, issues related to PAPR reduction in OFDM and MIMO-OFDM were addressed effectively.

Muller et al. [11] compared two PAPR reduction schemes for OFDM: selective mapping (SLM) and partial transmit sequence (PTS). They determined from the results that both methods did not impose the modulation of subcarriers and its number. Improved statistical results on multi-carrier transmit signal were obtained. A comparison was made in terms of system complexity and signal redundancy that were transmitted.

Ni et al. [12] proposed an adaptive tone reservation (ATR) method in the reduction of PAPR on multi-user MIMO. The tone reservation scheme was iteratively performed on the antenna with the maximum rate of

PAPR. The simulation results of the analysis proved that ATR has better results in the reduction of PAPR with minimum computational complexity than the existing conventional methods.

Anoh et al. [13] proposed a root-based non-linear method to reduce PAPR on OFDM, which is an extension of the standard μ-law companding (MC) method. In the study, the proposed method was evaluated using existing approaches, such as MC, log-based modified, exponential companding, and hyperbolic arc sine companding. The evaluated results in terms of BER indicated that the proposed DHT pre-coded RMC outperforms other algorithms.

Kim et al. [14] proposed a PAPR reduction method called PAPR reducing network (PRNet), which is based on the deep learning algorithm called auto encoder architecture. The deep learning method was used to determine the constellation mapping and demapping of subcarrier symbols. The environment was simulated for the evaluation based on BER, thereby obtaining reduced PAPR on OFDM. Aghdama et al. [15] proposed a reduced PAPR method based on PSO. The novel method searched the phase factors for its optimum to reduce the computation complexity and PAPR of OFDM.

Xu et al. [16] proposed a PAPR reduction method based on non-linear scaling with frequency modulation. In this method, high peak signal, which was larger than the threshold, was downscaled to reduce PAPR using frequency modulation combining OFDM. The result obtained lower bandwidth than that of existing algorithms. Therefore, the specified approach obtained lower PAPR with better BER performance than those of existing algorithms.

Ann et al. [17] compared the PAPR reduction techniques with the evaluation-based BER and CCDF. The specified method was compared with other applications, such as SLM, linear block coding (LBC), PTS, and peak insertion (PI) of OFDM at the transmitter. The analysis concluded that among the compared methods, PI was more effective than the other algorithms in reducing PAPR.

Kaur et al. [18] reviewed the PAPR reduction techniques on OFDM with the advantages and disadvantages of OFDM. The final analysis was performed with PAPR reduction based on computational complexity, bandwidth expansion, spectral spillage, and performance. Bakkas et al. [19] proposed a novel clipping method called palm clipping for PAPR reduction based on hyperbolic cosine. Simulations with the variations among the clipping ratio and modulation were analyzed with the evaluation of PAPR and BER. The result was obtained between 7 dB and 9 dB of the PAPR reduction based on modulation.

3 Proposed PAPR-DBNet Methodology

Owing to the nature of robustness in the propagation of multipath environments and low complexity design, OFDM has been widely used for wireless communication networks, such as LTE, 5G, and IEEE systems. However, an OFDM wireless system faces the issue of PAPR, thereby leading in the distortion of transmitted signal. To reduce PAPR, this study proposed a PTS-based deep learning based algorithm called deep belief network, which is also called PAPR-reduced DBNet. The system architecture is shown in Fig. 1.

3.1 OFDM System

In OFDM, input data signals are modulated into M orthogonal subcarriers and combined with IDFT at the transmitter end. The encoded symbols are transmitted over the signal. Samples of the input data are represented as $x_0, x_1, x_2, \ldots, x_m$. The data block with length m is represented as vector T as follows:

$$X = [X_0, X_1, \ldots, X_{M-1}]^T. \tag{1}$$

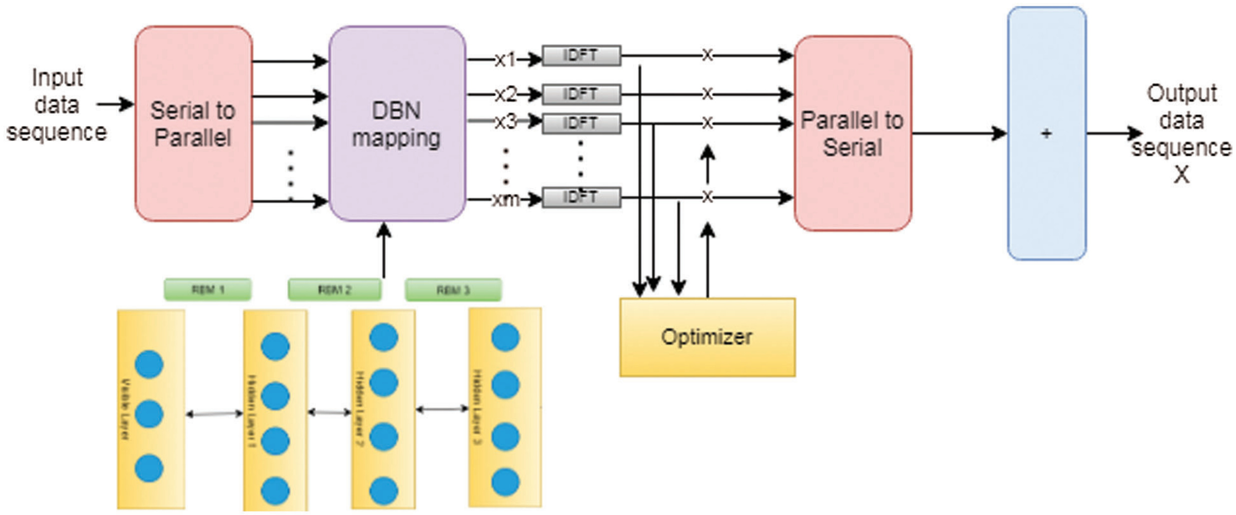

Figure 1: Proposed PAPR-DBNet architecture

The complex data block of the transmitted signal is represented as follows:

$$X(t) = \frac{1}{\sqrt{M}} \sum_{m=0}^{M-1} X_N e^{k2\pi m \Delta f t} 0 \leq t \leq MT, \tag{2}$$

where k = $\sqrt{-1}$, Δf is the sub-block space, and MT is the data block time.

3.2 PAPR

Numerous subcarriers/blocks in OFDM will increase PAPR [1–3]. PAPR is the relationship between maximum sample power and its equivalent average power. The high peak signal of OFDM after IDFT is based on input sequences, such as X_0, X_1,…, X_(M − 1). Statistically, it is represented as follows:

$$PAPR\{X_M\} = \frac{max[x_m]^2}{E[x_m]^2}. \tag{3}$$

E-Expectation operation. High PAPR signal will be linearly amplified through a non-linear amplifier and minimize the signal-to-noise ratio (SNR). Low PAPR will increase the SNR value. This power characteristics is represented using the following crest factor:

$$CF = \sqrt{PAPR\{X_M\}}. \tag{4}$$

The performance of PAPR is evaluated using the complementary cumulative distribution function (CCDF). CCDF refers to the probability of the OFDM signal that exceeds the threshold level of PAPR, and is written as follows:

$$CCDF = P(PAPR > PAPR_t) = 1 - \left(1 - e^{-PAPR_t}\right)^M. \tag{5}$$

3.3 Proposed PSO-Optimized DBNet for PAPR Reduction

Among the various deep learning algorithms, deep belief network has recently gained popularity in machine learning owing to its promised advantages. Fast implication and ability to handle large and high network structures are included in the beneficial aspects [20]. In DBB, the generative models consist of multiple layers in the hidden units. By contrast, DBNet consists of one visible layer and multiple hidden layers. The visible layer is responsible for transmitting input data to the hidden layers to complete the machine learning process [21]. It is based on restricted Boltzmann machine (RBM), and the RBM layer communicates with its previous and subsequent layers. Each RBM layer contains two sublayers (i.e., visible and hidden layers). The connection between the visible and hidden layers in RBM is restricted. The transformation process of data from visible to hidden layer is activated through sigmoid function based on the RBM learning rule [22]. The architecture consists of three stacked RBMs: RBM1 has a visible layer and a hidden layer 1, RBM2 has hidden layers 1 and 2, and RBM3 has a hidden layer 2 and a hidden layer 3.

In the DBN structure with stacked RBM, the training process of the DBN classifier is based on the training of each RBM with a learning rule. Parameters in connection with the training include the synaptic weight between the layers, bias, and states of neurons. The state of each neuron in each RBM is formed by transforming the bias and state of the neuron from the previous layer weight to the next layer. Sigmoid function is used for the following transformation:

$$P(s_i = 1) = \frac{1}{1 + \exp(-b_i - \sum_j s_j w_{ij})}. \tag{6}$$

Initially, the synaptic weight and bias of all neurons in the RBM layer are initialized. Each training of the input data consists of two phases (i.e., positive and negative phases). The positive phase converts data from visible to hidden layer, and the negative phase converts data from hidden to the corresponding visible layer. The corresponding activations of the positive and negative phases are calculated using Eqs. (7) and (8), respectively [23]:

$$P(v_i = 1|h) = sigm(-b_i - \sum_j h_j w_{ij}), \tag{7}$$

$$P(h_i = 1|v) = sigm(-c_i - \sum_j h_j w_{ij}). \tag{8}$$

When compared with the normal DBN, the weights parameters of the proposed method are optimized until the maximum number of epochs is reached. The training process continues and the parameters are optimized as follows:

$$update\left(w_{ij} + \frac{\eta}{2} \times \left(positive\left(E_{ij}\right) - negative\left(E_{ij}\right)\right)\right), \tag{9}$$

where

$positive\left(E_{ij}\right)$-Positive statistics of edge $E_{ij} = p(h_j = 1|v)$,

$negative\left(E_{ij}\right)$-Positive statistics of edge $E_{ij} = p(v_j = 1|h)$,

η-learning rate.

The preceding process is for the training of one RBM, and the same process will be repeated until all RBMs are trained. DBN was optimized using PSO to improve the proposed model of PAPR reduction. Kennedy et al. [24,25] developed PSO, which is a widely used optimization technique owing to its efficiency. In PSO, each individual of a population is called a particle, which consists of its position, velocity vector, and fitness value to control particle movement. On the bases of internal intelligence (pbest) and best experience (gbest), the position of each particle and velocity are changed at each iteration. Each particle performance is evaluated using predefined cost functions at the end of the iterations. Among the entire population, each particle takes the value of the neighbor particle, which is referred to as optimal global value called Gbest. The PSO process is calculated as follows:

$$v_i^{t+1} = wv_i^t + c_1.r_1\left(Pbest_i^t - X_i^t\right) + c_2.r_2\left(Gbest^t - X_i^t\right), \tag{10}$$

$$X_i^{t+1} = X_i^t + v_i^{t+1}, \tag{11}$$

where i = 1…, N is the number of swarm population, v_i^t is the velocity vector, t is the iteration, X_i^t is the current position of the ith particle, $Pbest_i^t$ is the previous best position of the ith particle, $Gbest^t$ is the previous best position of the entire particle, c_1 and c_2 are the coefficients called cognitive and social parameters, respectively, $r_1,\ r_2 \in [0,1]$ are random numbers, and w is the internal coefficient to control the local and global searches. Standard PSO can update the position of a particle as follows:

$$X_i = \begin{cases} 1 & if\ rand < s\left(v_i^{t+1}\right) \\ 0 & otherwise \end{cases}, \tag{12}$$

where s(v_i^(t + 1)) is the sigmoid function that will transform velocity in the range (0, 1), and rand ( ) is the random number selected from the distribution in the range [0,1]. A potential limitation of the standard PSO fitness function is that it may guide the PSO algorithm to search for a small feature subset with low classification performance instead of searching for a large feature subset with high classification performance. To overcome this limitation, the self-updating PSO fitness function is enhanced to produce the minimum set of features that will enhance the classification performance. Standard PSO has been updated with the evolutionary method called self-updating strategy (SUS) to include the heuristic to avoid wrong movement in the restricted region of particles. SUS of PSO uses inheritance probability tree (IPT) [26] to update the position of individuals in the population. These particles are updated using a self-updating mechanism. In terms of the standard PSO Eqs. (1) and (2), the terms are assumed as (i) present becomes gbest, (ii) present becomes pbest, (iii) present remains present, and (iv) present is assigned a value near gbest and pbest. Given the update, a term called popbest is included to indicate the best particle in the swarm population.

Normal fitness function in Eq. (4) is used to minimize the classification error during the training process [27]:

$$fitness\ function\ f = \frac{1}{PAPR(x)} \tag{13}$$

Algorithm 1: PSO-DBNet-PAPR
Input: Swarm Size M, Maximum Iteration t-max, Number of features/Particle dimension D, $r_1, r_2,\ c_1, c_2$, w and t = 1, initialize particles with random position
Output: phase factor with minimum PAPR
Step 1: for particle i = 1 to M do
Step 2: random initialization of position X_{id}^p with values and velocity vector V_{id}
Step 3: end for
Step 4: while t ≠ tmax
Step 5: for each particle i do
Step 6: Evaluate the position of the particle using Eq. (12)

(Continued)

Algorithm 1 (continued)

Step 7: Evaluate the fitness of each particle using Eq. (13)
Step 8: end for
Step 9: for i = 1 to M do
Step 10: update the pbest of particle i
Step 11: update the gbest of particle i;
Step 12: End for
Step 14: for particle i = 0 to M do
Step 15: for dimension D = 0 to D do
Step 16: change the velocity of particle using Eq. (10)
Step 17: change the position using Eq. (11)
Step 18: End for
Step 19: End for
Step 20: t = t + 1
Step 21: End While
Step 22: return the position of gbest
Step 23: Train the first layer of the RBM with the input of first hidden layer as h^0.
Step 24: while (epoch <= maxepoch)
Step 25: update weight and bias using the Eq. (9).
Step 26: the first layer representation is used for next layer as $P(h^1 = 1|h^0)$
Step 27: train the consecutive layer of RBM
Step 28: end while

In PTS, signal scrambling requires high computational complexity to determine the phase factor. Hence, PSO-based DBNet in this study was applied on the PTS transmitter on OFDM to reduce PAPR. Furthermore, PTS is one of the PAPR reduction mechanisms that splits data blocks into M-partitioned disjoined sub-blocks depending on the pseudo-random method [28,29]. For each block, IDFT is computed separately and weighted based on phase factor. The selected phase factor reduces the combined PAPR signal transmitted. Fig. 1 shows the OFDM transmitter with the PTS method. Input data block x_0, x_1, x_2, …, x_m are divided into orthogonal sub-blocks and represented as follows:

$$X = \sum_{m=1}^{M} X_m. \tag{14}$$

Sub-block $x_{m,1} \leq m \leq M$ is calculated and weighted using the phase factor $b_m = e^{k\varphi m}$, where $\varphi_{m,k} \in [0, 2\pi], 0 \leq 1 \leq M$. The minimized PAPR combined signal with phase factor and is represented as follows:

$$x = \sum_{m=1}^{M} b_m x_m. \quad (15)$$

The initial phase factor is adjusted as 1 to avoid loss of information. Thereafter, the M − 1 phase factors are returned.

4 Simulation Results and Discussions

The performance of the proposed PAPR reduction technique on OFDM wireless systems was evaluated in this section based on CCDF of the PAPR and BER performances. Simulations were based on the paper [14]. The used simulation parameters are listed in Tab. 1.

Table 1: Simulation parameters

Parameters	Specifications
Number of subcarriers	64
QAM modulation	4
Number of transmitted bits	256
Signal constellation	OFDM-QAM
Channel model	Rayleigh fading
Training samples	400
Total number of batches	500000
Weight parameter	0.02
Training rate	−13 dB

The proposed PAPR-reduced PSO-based DBNet was evaluated using conventional PAPR reduction schemes, such as the clipping method and PTS method with four sub-blocks and four phase factors considered for the comparative analysis. Given that the proposed algorithm was based on deep learning with evolutionary approach, the execution time of the algorithm was recorded as 390 µs for parallel computation and 1450 µs without parallel computation. Thus, the proposed algorithm was lower than the other conventional algorithms. The comparison of the execution time is shown in Tab. 2.

Table 2: Execution time comparison of the PAPR reduction methods

PAPR reduction mechanisms	Execution time (µs)
Clipping	1700
PTS	1900
Kim et al. [14]	2304
Aghdam et al. [15]	2108
Proposed PAPR PSO-DBNet	1950

The results of the evaluation in terms of execution time revealed that the proposed PAPR-PSO-DBNet obtains less time compared with the conventional and existing schemes of the PAPR reduction. The comparative analysis with regard to CCDF is shown in Fig. 2. The evaluation of the comparison in terms of BER is shown in Fig. 3.

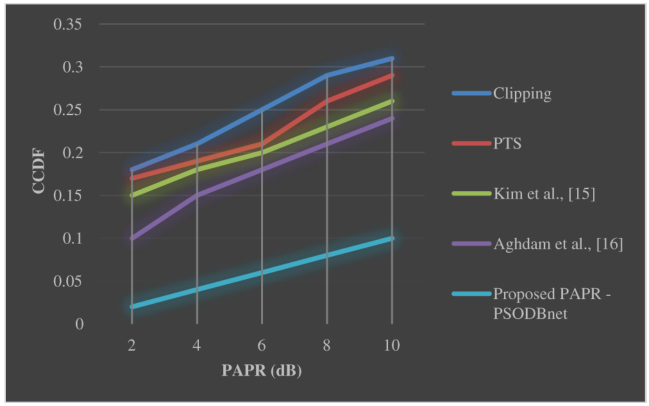

Figure 2: CCDF comparison of the different PAPR reduction schemes in 64 sub-blocks of OFDM

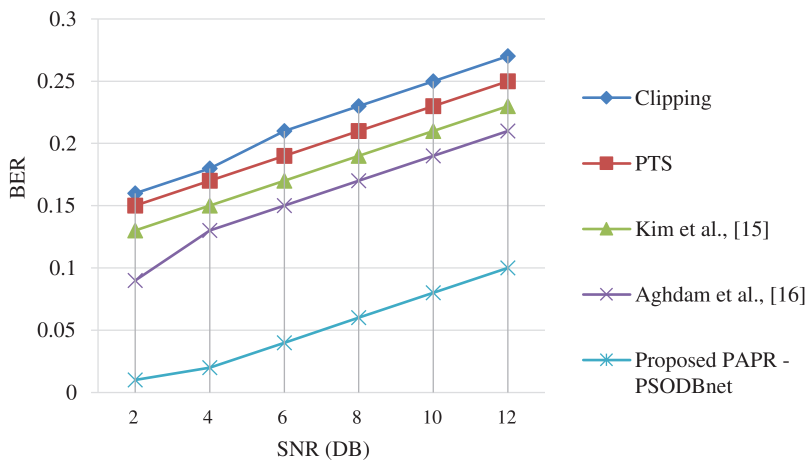

Figure 3: BER comparison of different PAPR reduction schemes in 64 sub-blocks of OFDM

The evaluation results illustrated in Fig. 2 shows the CCDF performances of various PAPR reduction schemes, such as clipping, with the proposed approach for all the data sequences. The proposed approach obtained less CCDF rate compared with the other existing approaches. Evidently, the proposed deep learning with evolutionary algorithm has been explicitly proven to reduce PAPR in OFDM transmitter on wireless communication systems.

The BER performances were compared for various PAPR reduction methods (Fig. 3). The proposed algorithm obtained low BER than the other existing algorithms. The original clipping method and PTS were unsatisfactory compared with the other methods because of distortion in the signal caused by the clipping effect. Hence, the proposed PSO-optimized DBnet exhibited superior performance in the reduction of PAPR in OFDM wireless systems. In addition, it is suited to 5G networks.

5 Conclusion

The 5G network makes every application move toward smart and innovative concepts. This study addressed the major signal distortion that impedes the 5G framework. Given the large transmission distances and weak communication network, signals are crunched before the target nodes receive the full data, thereby increasing the peak-to-average ratio in OFDM. PAPR may be reduced by avoiding distortion of signals in multidivisional frequency multiplexing network. In addition, this research provided a solution using PTS-based DBNet in the detection of loss area and fixing problems, thereby helping next generation wireless networks provide high performance communication system. The proposed PSO-based DBNet consumed 1950 micro sec to compute the data in 5G network. Although some of the traditional systems consume 1700 and 1900 µs, which are lower than that of PSO-DBNet, they suffer from BER. Similarly, the proposed system reduced SNR with less BER. In the future, the specified problem can be examined/tested using various machine learning techniques to enhance signal transmission.

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