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# An Efficient Low complexity PAPR Reduction Techniques Using Neural Networks

Feby Paulose[1] , Asst. Prof. Shiji Abraham[2]
[1](,ECE Dept , SNGCE ,India)
[2](ECE Dept , SNGCE ,India)

***Abstract:*** *In Long term evaluation (LTE) systems advanced wireless communication technique is used to minimize the Multiple Access Interference (MAI). Both transmitter and receiver are responsible for the better throughput and minimum error rate. Transmitter plays the major role and needs little efficient modification in terms of transmission power and modulation techniques. Minimum transmission power deliver the good results and it can be achieved by peak to average power ratio (PAPR) reduction with the help of soft computing techniques. In this letter, we propose a new method that uses NNs trained on the active constellation extension (ACE) signals to reduce the PAPR of OFDM signals. Unlike other NN based techniques, the proposed method employs a receiver NN unit, at the OFDM receiver side, achieving significant bit error rate (BER) improvement with low computational complexity*

***Keywords -*** *OFDM, PAPR, ACE, BPNN,Neural Networks.*

## I. Introduction

One of the popular modulation methods of digital communication is OFDM. Audio and TV broadcasting, internet access through broad band wireless networks and mobile communications (4G) uses OFDM as their modulation technique. However the average the fraction of multi carrier signals in the communication channel is often expressed in a quantity called PAPR. PAPR stands for Peak to average power ratio. PAPR is expressed as the ratio of maximum power to the average power. The relation between PAPR and the quality of the signal is inverse. Less the PAPR more is the signal quality. In the field of wireless communication several techniques are being researched for the reduction of the PAPR and is a hot spot.

To mitigate the occurrence of OFDM signals with large peak power, various PAPR reduction methods have been proposed such as the active constellation extension (ACE) technique [2]–[4]. The ACE scheme reduces the PAPR with low bit error rate (BER) by iterative time domain signal clipping and frequency domain constellation point extensions. Unfortunately, the ACE scheme requires a large number of inverse discrete Fourier transform (IDFT) and discrete Fourier transform (DFT) operations with slow convergence. In [5], a low complexity ACE method based on artificial neural network (NN) was proposed. The time frequency neural network (TFNN) PAPR reduction method, proposed in [5], achieves a close PAPR reduction performance compared to the ACE method with lower complexity. However, the TFNN scheme requires complex frequency domain NN modules and shows a poor BER performance in high order modulation fading channels. In this letter, we propose a novel PAPR reduction technique based on the ACE and NN techniques. The proposed scheme has much lower complexity and better BER performance compared to other ACE based methods with very small PAPR reduction performance loss.

## II. System Model

The incoming data symbol is first to be phase modulated. The modulation chosen for this is the QPSK. This gives us a signal in which two bits are modulated at once selecting one of four possible carries phase shift. Now the signal has to be converted to time domain and is thus followed by MN point IDFT where M is the over sampling factor. The signal is then clipped with a pre-defined threshold value. Since clipping would cause in-band-distortion and out-of-band radiation, we apply the resultant clipped signal to the NN for training and classification and then filtered.

The frequency domain data symbol vector with N sub carriers and over sampling rate of M with (M-1)N zeros in the middle is expressed as

$$\mathbf{X} = \left[\, X_0 \cdots X_{N/2-1}\ 0 \cdots 0\ X_{N/2} \cdots X_{N-1} \right]^T, \quad (1)$$

where *Xk* is the quadrature phase shift keying (QPSK) or quadrature amplitude modulation (QAM) modulated data symbol of *k*th subcarrier. The *n*th oversampled time domain

OFDM signal is expressed as

$$x_n = \frac{1}{\sqrt{JN}} \sum_{k=0}^{JN-1} X_k e^{j2\pi \frac{nk}{JN}},\ n = 0, 1, \ldots, JN-1 \quad (2)$$

where $N$ is the number of subcarriers. Equation (2) can be expressed as

$$\mathbf{x} = \mathbf{Q}^H \mathbf{X}, \quad (3)$$

where **Q** is the inverse discrete Fourier transform (IDFT) of size $JN \times JN$and $\mathbf{Q}H$ denotes the Hermitian of **Q**. The PAPR of the transmitted OFDM signal is defined as

$$PAPR = \frac{\max_{0 \le n \le JN-1} \{|x_n|^2\}}{E[|x_n|^2]}, \quad (4)$$

where $E[\cdot]$ denotes the expectation operator. The complementary cumulative distribution function (CCDF) of the PAPR of an OFDM signal is generally used to evaluate the performance of a PAPR reduction scheme. The CCDF of the PAPR for a given clip level $PAPR0$ is defined as

$$CCDF_{PAPR} = \Pr(PAPR > PAPR_0). \quad (5)$$

For the OFDM systems with Gaussian time domain signals, the CCDF of the PAPR can be expressed as

$$CCDF_{PAPR} = 1 - \left(1 - e^{-PAPR_0}\right)^N, \quad (6)$$

where $N$ is the number of subcarriers.

## III. Proposed NN Technique

### 3.1.ACE Scheme

In the ACE scheme, the PAPR is reduced through $L$ number of iterative processing between the time and frequency domain. The signal peaks are reduced by clipping the signals with magnitudes exceeding a certain target peak level in time domain and BER degradation is avoided in frequency domain by constraining the movement of the constellation points due to clipping to only acceptable extension directions.

### 3.2 TFNN Scheme

In the TFNN scheme, the PAPR is reduced by the use of two stage neural network architecture based on time domain neural network (TNN) for time domain processing and frequency domain neural network (FNN) for frequency domain processing. Both TNN and FNN are based on the multilayer feed forward network [6] with two layers and two neurons per layer with triangular activation function. The TFNN is trained using the ACE signal as the desired signal with the Levenberg-Marguardt algorithm [7] as the learning algorithm. The training procedure of the TFNN technique is
as follows [5].
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1) Obtain training input and desired signals for time domain processing: The time domain OFDM signal **x** is used as the training input signal to the TNN. The time domain ACE signal $\mathbf{x}ACE$ is used as the desired signal for neural weight adaptation process.
2) Train and construct real and imaginary TNN modules, *ModTNNRe* and *ModTNNIm* : The real and imaginary parts of the training input and desired signals are separated to be used as independent training input and desired signals for two different TNN module constructions.

3) Obtain training input and desired signals for frequency domain processing: The frequency domain TNN signal $\mathbf{X}TNN$ is obtained by applying DFT to the time domain TNN output. The frequency domain ACE signal $\mathbf{X}ACE$ is obtained by applying DFT to $\mathbf{x}ACE$. $\mathbf{X}TNN$ is used as the training input signal and $\mathbf{X}ACE$ is used as the training desired signal for training FNN.

4) Separate the training input and desired signal into four constellation regions: The divided signals are used to construct eight independent FNN modules, $Mod_{FNNRe,1q}$ , $Mod_{FNNIm,1q}$, $Mod_{FNNRe,2q}$ , $Mod_{FNNIm,2q}$, $Mod_{FNNRe,3q}$ , $Mod_{FNNIm,3q}$, $Mod_{FNNRe,4q}$ , $Mod_{FNN\ Im,4q}$, corresponding to each four quadrants.

5) Train and construct real and imaginary FNN modules for four constellation regions.

6) TFNN architecture is completed based on the TNN and FNN modules from previous steps.

**1.3 Proposed Scheme**

In the proposed scheme, the FNN unit is removed and an additional simple NN unit is employed at the receiver side as shown in Fig.1.

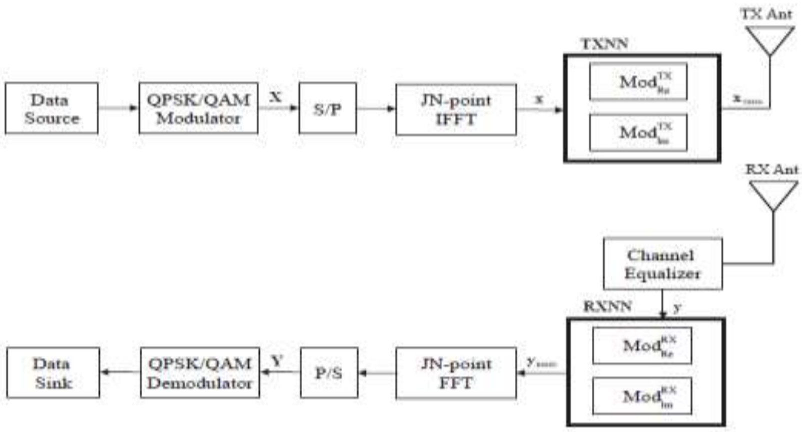


Fig. 1. Block diagram of the proposed scheme.

Reduction of complexity is realized by using a single time domain NN unit for PAPR reduction and BER performance improvement is achieved through the time domain NN unit at the receiver. The proposed transmitter NN (TXNN) and the receiver NN (RXNN) are based on the multilayer feedforward network with two layers and two neurons per layer with triangular activation function. The training procedure of the proposed NN scheme can be described as follows.
leftmargin=.5in

1) Obtain training input and desired signals for TXNN: The time domain OFDM signal **x** is used as the training input signal to the TXNN and the time domain ACE signal **x***ACE* is used as the desired signal.
2) Train and construct real and imaginary TXNN modules, *ModTXRe* and *ModTXIm* : The real and imaginary parts of the training input and desired signals are separated to be used as independent training input and desired signals.

3) Obtain training input and desired signals for RXNN: The time domain TXNN signal **x***TXNN* is used as the training input signal to the RXNN and the time domain OFDM signal **x** is used as the training desired signal.

4) Train and construct real and imaginary RXNN modules, *ModRXRe* and *ModRXIm* to be applied at the receiver side. The testing procedure of the proposed NN scheme is realized as follows.

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1) Obtain time domain OFDM signal **x**: The time domain OFDM signal is obtained by applying an IDFT to the modulated data symbols in **X**.

2) Obtain time domain TXNN signal **x***TXNN* : The trained
TXNN is applied to the OFDM signal to produce

$$\mathbf{x}_{TXNN} = Mod_{Re}^{TX}\{\mathbf{x}_{Re}\} + j\ Mod_{Im}^{TX}\{\mathbf{x}_{Im}\}.$$

3) At the receiver side, a quasi-static frequency selective Rayleigh fading channel with perfect channel estimation is assumed.
4) Obtain time domain RXNN signal **y***RXNN* : The trained RXNN is applied to the received signal with channel estimation to produce

$$\mathbf{y}_{RXNN} = Mod_{Re}^{RX}\{\mathbf{y}_{Re}\} + j\ Mod_{Im}^{RX}\{\mathbf{y}_{Im}\}.$$

**TABLE I**
**COMPUTATIONAL COMPLEXITY COMPARISON OF THE ACE, THE TFNN,AND THE PROPOSED SCHEMES WITH *N* = 128 SUBCARRIERS AND*L* = 20 ACE ITERATIONS**

| | ACE | TFNN | Proposed |
|---|---|---|---|
| (I)FFT | 40 | 2 | 1 |
| Complex Multiplications | 17920 | 896 | 448 |
| Complex Additions | 35840 | 1792 | 896 |
| NN | - | 10 | 4 |
| Real Multiplications | - | 10240 | 4096 |
| Real Additions | - | 7680 | 3072 |
| Feasible Region Check | 2560 | 128 | - |

**3.4. Complexity Analysis**

The computational complexity of the ACE, the TFNN, and the proposed schemes is compared in Table I. The table shows the number of complex multiplications and additions due to the use of (I)FFT modules, real multiplications and addition due to the use of NN modules, and the feasible region check operations. It is assumed that the number of complex multiplication and additions required of the $N$ point (I)FFT modules are ($N$/2) log2($N$) and $N$ log2($N$), respectively. Furthermore, the NN modules based on the multilayer feedforward network with two layers and two neurons per layer require 8$N$ real multiplications and 6$N$ real additions. In the ACE scheme, $L$ iterative processing of $N$ point IFFT computation is required for time domain clipping and additional $L$ iterative processing of $N$ point FFT computation is required for frequency domain constellation extension. In addition, $LN$ feasible region check operations are required to enforce acceptable extension constraint. In the TFNN scheme, one $N$ point IFFT computation is required for TNN processing and one $N$ point FFT computation is required for FNN processing. In addition, 2 NN computations are required for the real and imaginary TNN processing and 8 NN computations are required for the real and imaginary FNN processing. Also, $N$ feasible region check operations are required to enforce acceptable extension constraint. As for the proposed scheme, only one $N$ point IFFT computation is required for TXNN processing. Furthermore, 2 NN computations are required for the real and imaginary TXNN processing and additional 2 NN computations are required for the real and imaginary RXNN processing. However, no feasible region check operation is needed in the proposed scheme. From Table I, it can be seen that the proposed scheme reduces the computational complexity compared to other schemes in terms of the number of complex multiplications and additions, real multiplications and additions, and the check operations.

## IV. Simulation Results

In this section, the proposed NN algorithm was evaluated based on the PAPR reduction and the BER performance. In the simulations, the number of subcarriers was set to $N$ = 128 and the oversampling rate was set to $J$ = 4.
The frequency domain data symbols were modulated using the QPSK and 16-QAM constellations on each subcarrier. For comparison purposes, simulation results were obtained for
the original OFDM system, the traditional ACE scheme, theTFNN scheme, and the proposed NN scheme.

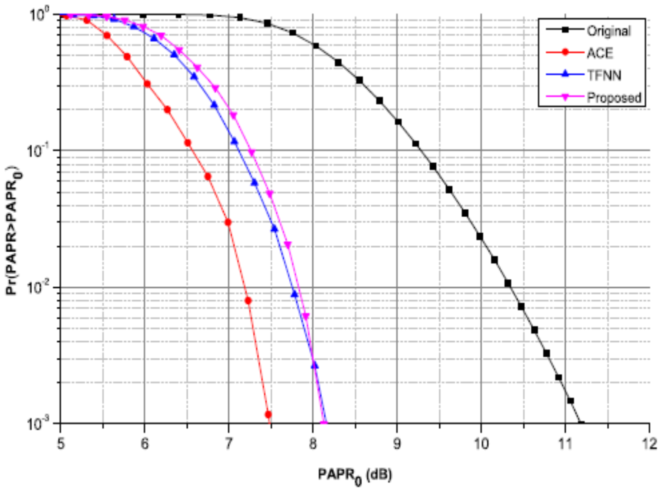


Fig. 2. CCDFs of the PAPR for original OFDM, ACE, TFNN, and the proposed method with $N$ = 128, $L$ = 20, and 16-QAM modulation

For the ACE method, the target clipping level A was set to 4.9 dB and the iteration were applied whenever the PAPR was greater than the target PAPR of 6 dB and the number of iterations was less than $L$ = 20.

The CCDF of the PAPR was used to evaluate the PAPR reduction performance of the proposed scheme compared to other schemes. It was observed that the ACE scheme, TFNN scheme, and the proposed NN scheme can significantly reduce the PAPR compared to the original OFDM signal for both QPSK and 16-QAM constellations. The TFNN scheme offers better PAPR reduction performance compared to the proposed NN scheme for low clip level *PAPR*0 values as shown in Fig. 2. This is because the TFNN employs additional complex frequency domain NNs to improve PAPR reduction and BER performance. However, the proposed NN scheme shows small performance loss, less than 0.25 dB, with much lower number of NN modules compared to the TFNN scheme.

Fig. 3 show the BER performances of the original OFDM system, the ACE scheme, the TFNN scheme, and the proposed NN scheme in the Rayleigh fading channel with QPSK and 16-QAM, respectively. The channel is assumed to be quasi-static frequency selective and perfect channel estimation is considered. It can be observed from that the ACE and NN based methods achieve BER improvement over the original OFDM signal due to the constellation extension, resulting in increased margin and lower error rates. Furthermore, the TFNN and the proposed NN schemes show better BER performance compared to the ACE scheme, demonstrating robust frequency domain processing.

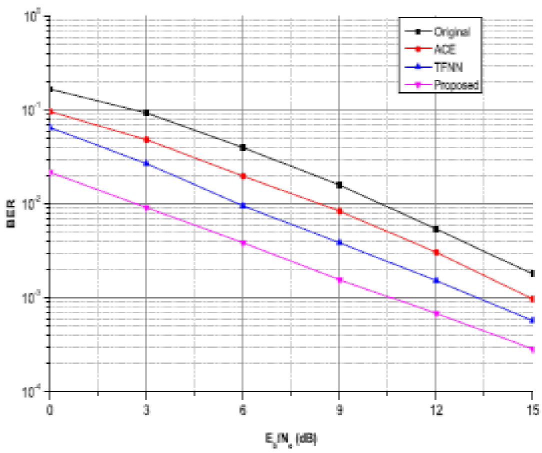


Fig. 3. BER performance for original OFDM, ACE, TFNN, and the proposed method with $N$ = 128, $L$ = 20, and QPSK in the Rayleigh fading channel.

## V. Conclusion

In this letter, we have proposed a novel ACE PAPR reduction method based on the transmitter NN and receiver NN with low computational complexity. From the simulation results, it was observed that the BER performance of the conventional ACE scheme is very poor than that of the original OFDM signal in Rayleigh fading channel with QAM modulation. The TFNN scheme was marginally better than the ACE scheme in the BER performance for high $Eb/N0$ values. However, the proposed scheme was shown to achieve a significant improvement in BER performance with similar PAPR reduction capacity compared to other ACE based techniques with lower complexity.

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