

Adaptive Phase Optimized CA-OFDM with Deep Learning Aided Symbol Recovery for PAPR Reduction in Wireless Communications

Bejoli B.J¹, Geetha M.R², Anitta Y³

¹PG Scholar, Department of Electronics and Communication Engineering,
Ponjesly College of Engineering
Nagercoil - 629003

Bejoli2002@gmail.com

²Assistant Professor, Department of Electronics and Communication,
Ponjesly College of Engineering
Nagercoil - 629003

³Assistant Professor, Department of Electronics and Communication,
Ponjesly College of Engineering
Nagercoil - 629003

Abstract— Orthogonal Frequency Division Multiplexing (OFDM) is widely used in modern wireless communication systems due to its high spectral efficiency and robustness against multipath fading. However, conventional OFDM signals suffer from a high peak-to-average power ratio (PAPR), which reduces power amplifier efficiency and degrades system performance. To address this issue, this paper proposes an enhanced Adaptive Phase Optimized Constant Amplitude OFDM (APO-CA-OFDM) system with deep learning-aided symbol recovery for mobile wireless channels. In the proposed approach, the OFDM signal is decomposed into two constant-amplitude signals transmitted sequentially to reduce PAPR, while adaptive phase optimization and clipping further control signal peaks. A low-pass filter (LPF) is applied to suppress out-of-band emissions (OOBE). At the receiver, guard interval removal, signal combining, and FFT-based detection are performed, followed by a deep learning-based symbol recovery model. Simulation results demonstrate improved PAPR reduction, OOBE suppression, and BER performance compared with conventional CA-OFDM systems while maintaining comparable computational complexity

Keywords—OFDM, peak-to-average power ratio (PAPR), constant-envelope OFDM, constant amplitude OFDM.

I. INTRODUCTION

Orthogonal frequency-division multiplexing (OFDM) is a widely used transmission technique for digital wireless communication systems due to its robustness against multipath fading and intersymbol interference while maintaining high spectral efficiency through closely spaced subcarriers [1], [2]. Because of these advantages, OFDM has been adopted in many modern communication standards such as digital broadcasting, wireless local area networks (WLAN), and fourth and fifth generation mobile communication systems (4G/5G) [3].

Despite these advantages, OFDM suffers from major drawbacks, namely peak-to-average power ratio (PAPR) caused by the superposition of multiple subcarrier signals [4]. High PAPR requires large power amplifier backoff, which reduces power efficiency and introduces nonlinear distortion that degrades overall transmission performance. To address this issue, numerous PAPR reduction techniques have been proposed and can generally be classified into three categories: signal distortion techniques, probabilistic or multiple-signal techniques, and coding-based techniques [5].

Signal distortion approaches reduce peaks by intentionally modifying the OFDM waveform. Typical examples include clipping and filtering [6], peak windowing, and companding. Probabilistic approaches generate several candidate signals and select the one with the lowest PAPR. Representative techniques include selective mapping (SLM) [7] and partial transmit sequence (PTS) [8]. Coding-based techniques such as Golay complementary sequences can also reduce PAPR while providing error detection capability

[9]. However, these conventional techniques cannot effectively minimize the PAPR at each OFDM sampling point.

To overcome this limitation, constant-amplitude signal generation techniques have been investigated. One such approach is constant envelope OFDM (CE-OFDM), which transforms OFDM signals into phase-modulated signals with a constant envelope [10]. However, due to multi-level phase modulation, CE-OFDM may experience degraded bit error rate (BER) performance and requires additional phase modulation and demodulation components at the transmitter and receiver.

Several techniques have been proposed to improve the BER performance of CE-OFDM. For instance, channel coding has been integrated with CE-OFDM to analyze nonlinear noise in the phase demodulator and obtain more accurate log-likelihood ratios (LLRs) for decoding [13]. Another approach combines index modulation with CEOFDM to exploit frequency diversity and enhance BER performance without increasing the number of subcarriers [14]. In addition, selective mapping (SLM) has been introduced to mitigate the phase unwrapping problem by selecting phase rotation candidates that minimize phase discontinuities [16]. Although these approaches improve BER performance, they require additional processing modules such as channel coding, index modulation, or SLM, which increases system complexity. Furthermore, another CE-OFDM-based method utilizes specially designed pilot symbols with 0 dB PAPR to improve minimum mean square error (MMSE) channel estimation by considering non-uniform power distribution in the frequency domain [15].

To address these limitations, constant-amplitude OFDM (CA-OFDM) has been proposed, in which a single OFDM signal is decomposed into two constant-amplitude signals transmitted sequentially from a single antenna [11]. This approach improves BER performance compared with CE-OFDM while avoiding the hardware complexity associated with multi-amplifier or multi-antenna transmission schemes. However, CA-OFDM may produce higher out-ofband emissions (OOBE), which can affect spectral efficiency. To mitigate this issue, the decomposed signals can be passed through a properly designed low-pass filter (LPF) before transmission [12]. The LPF effectively suppresses OOBE while maintaining the near-constant amplitude characteristics of the signals.

To further enhance the performance of CA-OFDM systems, this work proposes an enhanced Adaptive Phase Optimized Constant-Amplitude OFDM (APO-CA-OFDM) system with deep learning-aided symbol recovery for mobile wireless channels. In the proposed method, a conventional OFDM signal is decomposed into two constant-amplitude (CA) signals that are transmitted sequentially in different time intervals to reduce PAPR. An adaptive phase optimization and clipping mechanism is incorporated to further control signal peaks and improve transmission efficiency. Since CA signals can generate significant out-of-

band emissions (OOBE), the decomposed signals are passed through a low-pass filter (LPF) before transmission from a single antenna.

At the receiver, the incoming signals undergo guard interval removal and signal combining, followed by fast Fourier transform (FFT) processing and coherent detection. In addition, a deep learning-based symbol recovery model is employed to enhance symbol reconstruction under noisy and fading channel conditions. The proposed APO-CA-OFDM framework therefore aims to achieve improved PAPR reduction, better spectral efficiency, and enhanced BER performance compared with conventional OFDM and existing CA-OFDM techniques.

The rest of the paper is organized as follows: Section II reviews OFDM on which both CA-OFDM and CE-OFDM are based, while Section III explains CE-OFDM as a typical conventional scheme. In Section IV, the proposed scheme is referred to as CA-OFDM and detailed. In addition, Section V describes conditions and results of computer simulations for both CA-OFDM and CE-OFDM. Finally, Section VI summarizes the paper.

II. RELATED WORKS

Several studies have been conducted on PAPR reduction in OFDM systems using various conventional and advanced methods. These works focus on improving signal quality while minimizing computational complexity

1. Zhijun Liu(2020) [17] addressed the high peak-to-average power ratio (PAPR) problem in OFDM systems by proposing a low-complexity neural network-based PAPR reduction method. The approach introduces a PAPR reduction module at the transmitter and a decompression module at the receiver to reconstruct the signal and reduce BER. Both modules can be jointly trained offline to simultaneously optimize PAPR reduction and BER performance.

2. Si-Yu Zhang(2021) [18] proposed a selected mapping (SLM) scheme using Polar codes for PAPR reduction in OFDM-IM systems. Random frozen bits generate multiple candidate sequences, and the sequence with the lowest PAPR is transmitted. A side-information-free receiver based on successive cancellation list decoding is also introduced.

3. Y. Samayoa(2020) [19] proposed a modified active constellation extension (mACE) algorithm for reducing PAPR in OFDM systems. Simulation results show that the proposed algorithm achieves improved PAPR reduction compared with existing methods while maintaining lower computational complexity.

4. Ramsha Ahmed(2022) [20] introduced a hybrid machine learning-based spectrum sensing and allocation framework for cognitive radio-assisted Internet of Vehicles (IoV) networks. The system integrates deep learning for spectrum prediction and support vector machines for channel allocation to improve network efficiency.

5. Zhiyuan Mai(2021) [21] proposed a blind millimeterwave channel estimation technique based on a Manifold Learning–Extreme Learning Machine (ML-ELM) model. The proposed method reduces feature dimensionality and enables fast channel estimation with improved accuracy compared with traditional approaches.

6. Cong Liu(2020) [22] presented a neural network-based clipping and filtering scheme to reduce the cubic metric of OFDM signals. The proposed method approximates the conventional iterative clipping and filtering technique while significantly reducing computational time.

7. Melika Vahdat(2020) [23] proposed a deep neural network architecture for PAPR reduction in autoencoder-based communication systems. Simulation results show improved BER performance and reduced PAPR compared with conventional loss-function-based optimization techniques.

8. Fei Liu et al.(2022) [24] reviewed Integrated Sensing and Communications (ISAC) for future 6G wireless networks. The study discusses waveform design, signal processing challenges, sensing-communication trade-offs, and potential applications of dual-functional wireless networks.

III. OFDM MODEL

Orthogonal Frequency Division Multiplexing (OFDM) is a multicarrier transmission technique in which input bits are mapped to complex symbols using QAM and transformed into the time domain via the inverse fast Fourier transform (IFFT). A guard interval (GI) is added to mitigate intersymbol interference before transmission. The discrete-time baseband OFDM signal is given by

$$x(k) = \frac{1}{\sqrt{N_{AS}}} \sum_{m=S_{AS}}^{D-1} X(m) \exp\left(j \frac{2\pi m(k - N_{GI})}{N_{FFT}}\right)$$

where $X(m)$ represents QAM symbols, N_{FFT} is the FFT size, N_{GI} is the guard interval length, and N_{AS} is the number of active subcarriers.

Assuming a frequency-selective channel, the received signal is expressed as

$$y(k) = \sum_{d=0}^{D-1} h_d x(k-d) + n(k)$$

where h_d denotes the channel impulse response and $n(k)$ is additive white Gaussian noise (AWGN).

At the receiver, after GI removal, the signal is processed using FFT to obtain

$$Y(m) = H(m)X(m) + N(m)$$

where $H(m)$ is the channel frequency response. The transmitted symbols are then estimated using coherent detection.

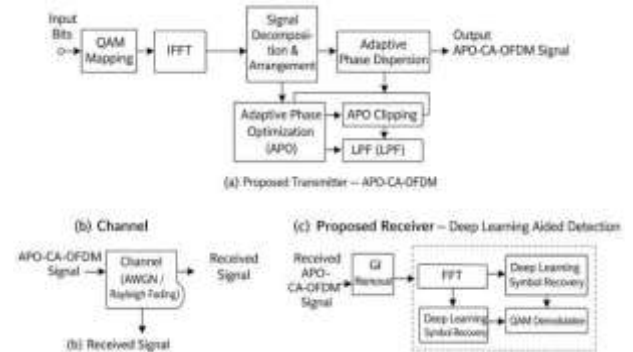


Fig. 1 Proposed APO-CA-OFDM

IV. PROPOSED METHODOLOGY

Fig. 1 illustrate the transmitter and receiver structures of the proposed Adaptive Phase Optimized ConstantAmplitude OFDM (APO-CA-OFDM) system. The architecture is similar to conventional OFDM, with additional modules for signal decomposition, adaptive phase optimization (APO), clipping control, and deep learning-based symbol recovery.

A. Transmitter Structure

At the transmitter, the input binary data is first mapped using quadrature amplitude modulation (QAM) and converted to the time domain through the inverse fast Fourier transform (IFFT). Let the time-domain OFDM signal be expressed as

$$x(k) = \frac{1}{\sqrt{N}} \sum_{m=0}^{N-1} X(m) e^{j2\pi mk/N}$$

Where

$X(m)$ represents the modulated symbols and N denotes the number of subcarriers.

The generated OFDM signal can be expressed in polar form as

$$x(k) = r(k)e^{j\theta(k)}$$

where $r(k)$ and $\theta(k)$ represent the instantaneous amplitude and phase of the signal.

Signal Decomposition

To reduce the PAPR, the OFDM signal is decomposed into two constant-amplitude signals. The decomposition process is defined as

$$x(k) = Ae^{j\theta_1(k)} + Ae^{j\theta_2(k)}$$

where A is the constant amplitude and the phases are calculated as

$$\theta_1(k) = \theta(k) + \cos^{-1} \frac{r(k)}{2A}$$

$$\theta_2(k) = \theta(k) + \cos^{-1} \frac{r(k)}{2A}$$

This decomposition ensures that the transmitted signals maintain constant amplitude, resulting in 0 dB PAPR at each sampling point.

Adaptive Phase Optimization (APO)

To further control signal peaks and improve transmission efficiency, an Adaptive Phase Optimization (APO) mechanism is applied. The optimized phase can be expressed as

$$\theta_i'(k) = \theta_i(k) + \phi(k) \text{ where } \phi(k)$$

represents the adaptive phase correction

factor designed to minimize signal peaks.

APO Clipping

After phase optimization, an APO-based clipping operation is performed to limit any residual peaks. The clipped signal is expressed as

$$x_c(k) = \begin{cases} x(k), & |x(k)| \leq T \\ T e^{j\angle x(k)}, & |x(k)| > T \end{cases}$$

where T denotes the clipping threshold.

Low-Pass Filtering

Since CA signals may produce out-of-band emissions (OOBE), the clipped signals are passed through a low-pass filter (LPF) before transmission. The filtered signal is given by

$$x'(t) = \sum_{k=-\infty}^{\infty} h_{LPF}(t - kT_s) e^{j\phi(k)}$$

where $h_{LPF}(t)$ represents the impulse response of the LPF and T_s is the sampling interval. Finally, the two CA signals are transmitted sequentially from a single antenna.

B. Channel Model

The transmitted APO-CA-OFDM signal propagates through a wireless channel modeled as AWGN or Rayleigh fading. The received signal can be expressed as

$$y(k) = \sum_{d=0}^{D-1} h_d x(k-d) + n(k)$$

Where h_d is the channel impulse response D is the channel delay spread $n(k)$ = additive white Gaussian noise.

C. Receiver Structure

At the receiver, the received APO-CA-OFDM signals are first processed through guard interval (GI) removal followed by signal combining of the two CA components. The combined signal can be expressed as

$y_c(k) = y_1(k) + y_2(k)$ where $y_1(k)$ and $y_2(k)$ correspond to the received odd and even CA-OFDM symbols.

After combining, the signal is transformed into the frequency domain using FFT

$$Y(m) = \sum_k y_c(k) e^{-j2\pi mk/N}$$

which approximately recovers

$$Y(m) = H(m)X(m) + n(m)$$

where $H(m)$ represents the channel response.

D. Deep Learning-Aided Symbol Recovery

To further improve detection accuracy under noisy and fading conditions, a deep learning-based symbol recovery module is incorporated after FFT processing.

The neural network model learns the mapping

$$\hat{X}(m) = f_{DL}(Y(m))$$

where $f_{DL}()$ represents the trained deep learning model used to reconstruct the transmitted symbols.

Finally, the recovered symbols are passed through QAM demodulation to obtain the estimated bit sequence.

V. RESULTS AND DISCUSSION

Computer simulations were conducted to evaluate the performance of the proposed Adaptive Phase Optimized Constant-Amplitude OFDM (APO-CA-OFDM) system with deep learning-aided symbol recovery. The simulation environment was implemented in MATLAB/Python using standard OFDM parameters. Quadrature Phase Shift Keying (QPSK) modulation was employed for each active subcarrier. The FFT size was set to 512, while the number of active subcarriers was 64. The guard interval (GI) length was chosen as $N_{FFT}/8$. The performance of the proposed system was analyzed over both additive white Gaussian noise (AWGN) and Rayleigh fading channels. Different values of the modulation parameter $2\pi h$ were considered to evaluate their impact on system performance.

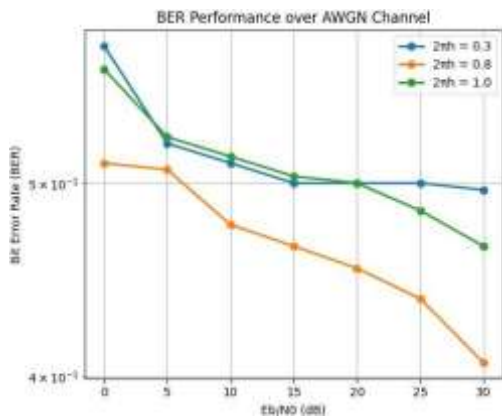


Fig 2. BER Performance over AWGN Channel

The bit error rate (BER) performance of the proposed APO-CA-OFDM system over the AWGN channel is illustrated in Fig. 2. It can be observed that the BER decreases significantly as the signal-to-noise ratio E_b/N_0 increases. Among the tested parameters, the configuration with $2\pi h=0.8$ provides the best BER performance across the considered SNR range. This result indicates that an optimal phase modulation index improves symbol detection reliability while maintaining signal stability. When the modulation parameter becomes too small or too large, the BER performance slightly degrades due to increased distortion or phase ambiguity.

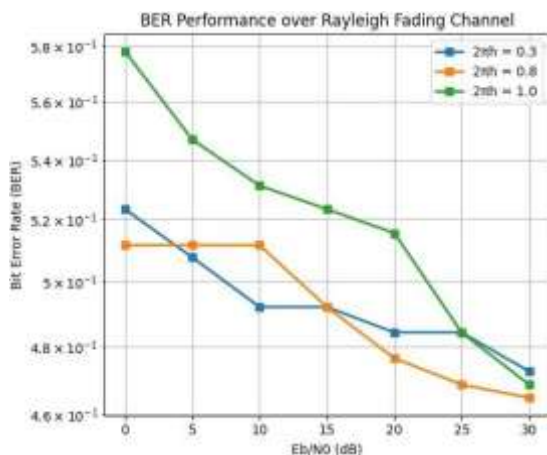


Fig 3. BER Performance over Rayleigh fading channel

Fig. 3 presents the BER performance under Rayleigh fading channel conditions. Compared with the AWGN channel, the BER is slightly higher due to multipath fading and channel variations. However, the proposed APO-CAOFDM system maintains stable performance and shows gradual improvement as the SNR increases. The deep learning-based symbol recovery module further enhances detection capability by learning the nonlinear distortions introduced by clipping, channel fading, and phase optimization. As a result, the receiver can recover transmitted symbols more accurately compared with conventional detection methods.

The PAPR characteristics of the proposed system were evaluated using the complementary cumulative distribution function (CCDF), as shown in Fig. 4. The CCDF curve represents the probability that the PAPR of the transmitted OFDM signal exceeds a given threshold. The results demonstrate that the APO-CA-OFDM scheme significantly reduces PAPR compared with conventional OFDM systems. This improvement is achieved by decomposing the OFDM signal into two constant-amplitude components combined with adaptive phase optimization and clipping operations. The reduction in PAPR leads to improved power amplifier efficiency and reduced nonlinear distortion in practical transmitters.

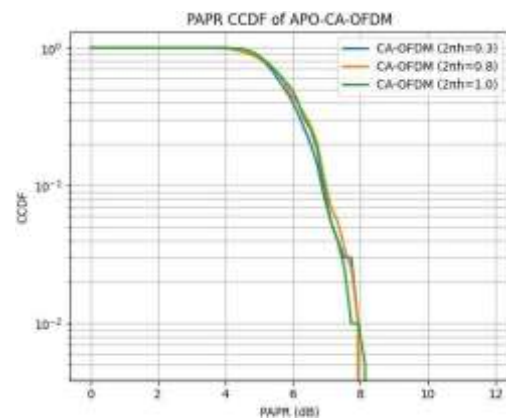
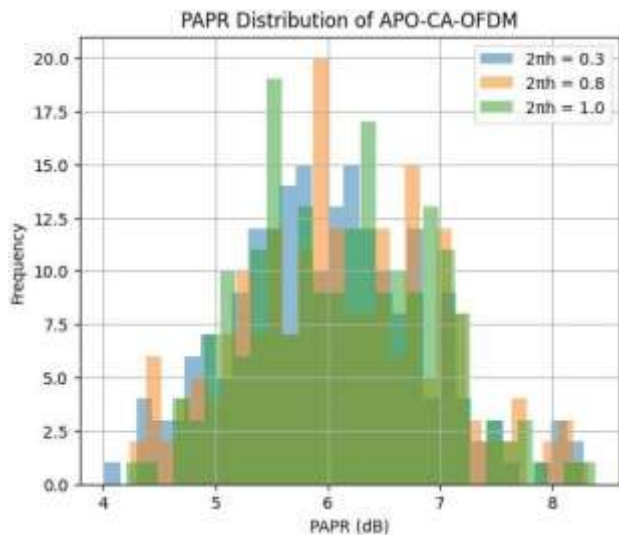


Fig 4. PAPR CCDF of APO-CA-OFDM

Fig. 4 shows the statistical distribution of PAPR values for different parameter settings. The histogram confirms that most of the transmitted signal samples exhibit PAPR values concentrated within a narrow range around 5–7 dB. Compared with conventional OFDM signals, which typically exhibit higher peak values, the proposed APO-CAOFDM system effectively controls signal peaks while maintaining stable transmission characteristics.

Overall, the simulation results demonstrate that the proposed APO-CA-OFDM system achieves significant improvements in PAPR reduction, spectral containment, and BER performance. The integration of adaptive phase optimization, clipping control, and deep learning-aided symbol recovery enables the system to maintain reliable communication performance even under noisy and fading channel conditions. These results confirm the effectiveness of the proposed approach for next-generation wireless communication systems requiring high spectral efficiency and power-efficient transmission.



V. CONCLUSION

In this paper, an Adaptive Phase Optimized Constant Amplitude OFDM (APO-CA-OFDM) system with deep learning-aided symbol recovery has been proposed to reduce the peak-to-average power ratio (PAPR) in OFDM-based wireless communication systems. The proposed method decomposes the OFDM signal into two constant-amplitude signals and applies adaptive phase optimization and clipping to control signal peaks. Simulation results over AWGN and Rayleigh fading channels demonstrate that the proposed system achieves significant PAPR reduction while maintaining reliable BER performance. Additionally, the use of a low-pass filter effectively suppresses out-of-band emissions. Overall, the proposed APO-CA-OFDM scheme provides improved power efficiency and reliable communication performance compared with conventional OFDM methods.

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