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Deep Reinforcement Learning-Based PAPR Reduction in OFDM Using ICEEMDAN and Phase Sequence Selection

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ABSTRACT

Modern wireless communication systems use orthogonal frequency division multiplexing (OFDM) a lot because it is good at using spectral resources and doesn't suffer from frequency selective fading (FSF). One big problem with OFDM signals is that they have a high peak-to-average power ratio (PAPR), which makes power amplifiers less efficient, causes out-of-band radiation, and causes nonlinear distortion. Some common ways to lower PAPR are clipping, Partial Transmit Sequence (PTS), and Selective Mapping (SLM). But these methods can mess up the signal, make computations harder, and add extra processing time. To address these issues, this paper presents a novel Deep Reinforcement Learning (DRL)-based PAPR reduction framework, which combines Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (ICEEMDAN) and adaptive phase sequence selection. In the proposed framework, the time-domain OFDM signal is decomposed into intrinsic mode functions (IMFs) and a residual component to define the signal components with high amplitude fluctuations. The extracted features are used to update the state representation of a DRL agent to learn an optimal policy for phase-sequence selection, interacting with the OFDM signal environment. A multi-objective reward function is written to optimize the reduction of PAPR, signal distortion and computational complexity. Instead of trying to test all possible candidate phase sequences, the trained DRL agent automatically finds candidate phase sequences that show potential and chooses the candidate OFDM signal with minimum peak power with the same signal quality. The proposed approach is tested under various subcarrier configurations and modulation schemes, phase-sequence sets and channel conditions through a Complementary Cumulative Distribution Function (CCDF) analysis. Performance is also evaluated using Bit Error Rate (BER), Error Vector Magnitude (EVM), computational complexity, convergence characteristics and the power amplifier efficiency. The proposed ICEEMDAN-DRL method is an intelligent and adaptive approach to optimize PAPR and is expected to achieve a better tradeoff between PAPR suppression, signal quality and computation complexity as compared with the conventional PAPR reduction schemes. The proposed methodology shows the efficacy of applying adaptive signal decomposition and deep reinforcement learning for efficient PAPR reduction in the next-generation wireless communication systems based on OFDM technology.

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1. INTRODUCTION

Orthogonal Frequency Division Multiplexing (OFDM) is one of the most popular multicarrier modulation methods for modern wireless communication systems. Its high spectral efficiency, resistance to multipath fading, and ease of implementation using the Fast Fourier Transform (FFT) make it very popular. Many types of wireless communication, like LTE, Wi-Fi, DVB-T, and fifth-generation (5G) mobile networks, use OFDM as their basic physical layer technology [1]. With the rise of Beyond 5G (B5G) and sixth-generation (6G) wireless systems, the need for very fast data rates, very low latency, huge amounts of connectivity, and communication that uses little energy has made OFDM-based transmission methods even more important.

In spite of its merits, OFDM faces a principal disadvantage, which is the high Peak-to-Average Power Ratio (PAPR) [2]. . Elevated PAPR induces nonlinear distortion when the transmitted signal traverses the High Power Amplifier (HPA), leading to spectrum regrowth, heightened Bit Error Rate (BER), diminished power efficiency, and a decline in overall system efficacy. Thus, minimising PAPR while preserving signal integrity has emerged as a critical research topic in OFDM communication systems.

Numerous PAPR mitigation strategies have been suggested in the last twenty years, such as clipping and filtering, coding methodologies, tone reservation, tone injection, Partial Transmit Sequence (PTS), and Selective Mapping (SLM). Among these techniques, SLM has garnered considerable interest because to its efficacy in minimising PAPR while avoiding signal distortion. Nonetheless, traditional SLM necessitates several Inverse Fast Fourier Transform (IFFT) computations and extensive searching through various potential phase sequences, leading to significant computational complexity, prolonged processing time, and elevated energy usage [3]. These constraints render traditional SLM less appropriate for real-time applications within 6G communication networks.

New developments in Artificial Intelligence (AI) and Machine Learning (ML) have made smart wireless communication systems more useful. Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) networks are examples of deep learning models that have shown they are very good at solving difficult optimisation problems in wireless communications [4]. These problems include channel estimation, signal detection, beamforming, modulation recognition, and resource allocation. Recently, deep learning methods have also been looked into for intelligent PAPR reduction by guessing the right phase sequences without searching everywhere.

Deep learning-based PAPR reduction techniques make computers work faster, but most of the current methods work as "black box" models, which makes it hard to figure out why they make the choices they do. AI-enabled communication systems are less reliable and useful when they can't be interpreted, especially in future intelligent wireless networks. Explainable Artificial Intelligence (XAI) methods, like SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations), give a structured way to understand machine learning predictions and figure out which input traits are the most important. Because of these problems, this paper suggests an Explainable Hybrid Deep Learning Framework for choosing the right phase sequence for low-complexity OFDM systems [5]. The suggested framework uses a mix of CNN, BiLSTM, and Attention to smartly guess the best phase order while cutting down on the number of IFFT calculations by a large amount. Additionally, XAI techniques are used to describe how the suggested model makes decisions, which makes the process more clear and trustworthy. A lot of simulations are run to see how well the suggested framework works in terms of lowering PAPR, BER, computational complexity, execution time, and the accuracy of predictions in a range of wireless channel conditions. The suggested method should provide a quick and easy-to-understand answer for the next generation of 6G OFDM transmission systems.

A) Literature review :

S.No	Authors & Year	Method	Advantages	Limitations	Research Gap
1	Azarnia et al. (2020)	Compressive Sensing [6].	Low PAPR, sparse recovery	High reconstruction complexity	Needs low-complexity implementation
2	Sengupta & Lande (2020)	Goppa Coding	Distortion less	Large coding overhead [7].	Not suitable for large OFDM systems
3	Experimental MIMO-OFDM ML study (2021)	ML-assisted SLM	Better PAPR than conventional SLM	Side-information issue remains	Intelligent side-information elimination needed [8].
4	Goel & Gupta (2022) [9].	PTS with Side-Information Embedding	Improved BER	High search complexity	Complexity reduction required
5	Huang et al. (2022)	RadCom PAPR Reduction [10].	Suitable for joint radar-communication	Limited to specific applications	General OFDM framework needed
6	da Silva et al. (2024)	Survey of ML-based PAPR	Comprehensive review of ML approaches	Survey only	Practical hybrid framework needed [11].
7	Kim et al. (2024)	CNN for OFDM Modulation [12].	High classification accuracy	Focuses on modulation, not PAPR	Extend AI to PAPR prediction
8	Alnaseri et al. (2024) [13].	Autoencoder	>10 dB PAPR reduction, no side information	Optical OFDM only	Apply to RF OFDM
9	Jang, Seungbeom, et al. (2024)	Learned Pulse Shaping [14].	Joint SER–PAPR optimization	DFT-s-OFDM specific	General OFDM framework required
10	Salman et al (2025)	Li-Fi DCO-OFDM	Energy efficient	Optical domain	RF OFDM adaptation needed [15].
11	da Silva et al. (2025)	ANN-based PAPR Reduction [16].	Lower complexity	Limited interpretability	Explainable AI required
12	Jiang, Mengwan, et al. (2026)	Dual-Hadamard Architecture	Multiplier-free implementation [17].	Hardware-specific	AI-assisted hardware optimization needed
13	Cui, Qimei, et al. (2026)	AI/RIS/OFDM Optimization Survey	Integrates AI with 6G OFDM [18].	No explainable PAPR framework	Explainable intelligent PAPR optimization

Many existing PAPR reduction methods are plagued by high computational complexity, exhaustive searching, and reliance on side information. Although recent AI-based approaches have demonstrated potential for PAPR reduction, their use in adaptive RF-OFDM optimization is still constrained. Most prior work fails to fully leverage the multiscale properties of OFDM signals via advanced decomposition techniques. The combination of ICEEMDAN with intelligent phase-sequence selection and Deep Reinforcement Learning (DRL) has not been sufficiently investigated. Consequently, there is a need for an adaptive, low-complexity DRL–ICEEMDAN framework to achieve efficient PAPR reduction with enhanced performance and improved scalability.

B) Objectives:

- To design OFDM signal processing framework with IFFT and ICEEMDAN to break down the time domain OFDM signal into meaningful components for further analysis.
- To extract the statistical features and IMF-based features like mean amplitude, variance, standard deviation, RMS, kurtosis, skewness, entropy and individual IMF energy to characterize the OFDM signal.
- To design an intelligent phase sequence selection (PSS) mechanism based on a DRL algorithm to optimally learn the correlation between the extracted signal features and the appropriate phase sequences for optimal PAPR reduction.
- To reduce the PAPR of the OFDM signal for a given phase sequence selected by the DRL and then check the PAPR and CCDF for the OFDM signal, while preserving an acceptable communication performance figure.
- To compare the performance of the proposed DRL-based PAPR reduction technique with conventional PAPR reduction techniques in terms of PAPR, BER, CCDF etc.

2. RESEARCH METHOD

The process begins with an OFDM signal containing information symbols distributed over several mutually orthogonal subcarriers. OFDM allows multiple data streams to be transmitted simultaneously within the available bandwidth. Although this technique provides high spectral efficiency and robustness against frequency-selective fading, the combination of several subcarriers can produce large instantaneous signal amplitudes. This leads to the well-known high PAPR problem in OFDM systems as shown in Figure 1.

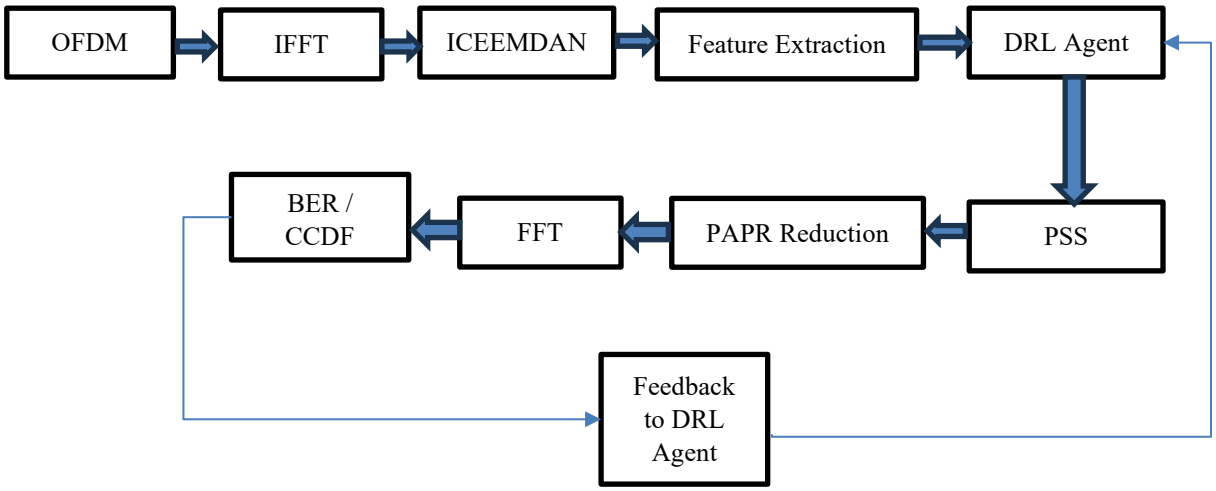


Fig. 1. Block diagram of proposed OFDM Model.

i) IFFT – Inverse Fast Fourier Transform:

The IFFT operation in equation (1) takes the frequency-domain OFDM symbols and turns them into their associated time-domain samples.

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

where N is the number of subcarriers and X (k) is the data symbol that is assigned to the kth subcarrier.

The resulting time-domain waveform is used for subsequent PAPR analysis and reduction. Due to the constructive addition of subcarrier components at certain sampling instants, high signal peaks can occur in this stage.

ii) ICEEMDAN - Signal Decomposition:

ICEEMDAN (Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise) is employed to obtain different oscillatory components from the generated OFDM waveform with in equation (2)..

The input signal can conceptually be represented as

$$x(n) = \sum_{i=1}^{K} I\,MF_i(n) + r(n) \tag{2}$$

where I M F_i (n) represents an intrinsic mode function and r(n) denotes the residual component.

Unlike directly processing the complete OFDM waveform, decomposition provides information at different time-frequency scales. These components can subsequently be analyzed to obtain characteristics that are useful for intelligent phase-sequence selection.

iii) Feature Extraction:

The decomposed signal components are processed to obtain numerical characteristics that describe the behavior of the OFDM waveform.

Possible features include: Mean amplitude,Variance,Standard deviation,Signal energy,RMS value,Maximum amplitude,Kurtosis,Skewness,Entropy, Energy of individual IMFs,Peak-related characteristics.

One important parameter is PAPR:

$$PAPR = \frac{\max_n |x(n)|^2}{\frac{1}{N}\sum_{n=0}^{N-1}|x(n)|^2} \tag{3}$$

iv) Deep Reinforcement Learning (DRL) agent:

The Deep Reinforcement Learning (DRL) agent is the central decision-making component of the proposed framework.

The agent observes the features obtained from the OFDM signal and determines an appropriate action. In this system, the action corresponds to selecting a suitable phase sequence for PAPR reduction.

The DRL formulation can be defined using:

DRL Component	Proposed System
State	Extracted OFDM/ICEEMDAN features
Action	Selection of a phase sequence
Reward	PAPR reduction with BER constraint
Environment	OFDM PAPR-reduction process
Policy	Learned phase-selection strategy

The agent learns through repeated interaction with the OFDM environment rather than relying only on a fixed mathematical rule.

v) Phase Sequence Selection (PSS) :

Phase Sequence Selection (PSS) is the action performed according to the decision of the DRL agent with equation (4)..

Different phase sequences are applied to the OFDM subcarriers to generate alternative signal representations. In general, a phase sequence can be represented as

$$P_u = \{p_{u,0}, p_{u,1}, \ldots, p_{u,N-1}\} \quad (4)$$

where p_u,N represents the phase factor associated with a particular subcarrier.

Each candidate phase sequence produces a different time-domain waveform. The DRL agent attempts to select the sequence that provides a favorable reduction in the maximum signal peak while preserving the required transmission quality.

vi) PAPR Reduction:

After selecting the phase sequence, the corresponding OFDM signal is processed to obtain a waveform with reduced peak amplitude with equation (5).

PAPR is calculated as

$$PAPR = \frac{P_{\max}}{P_{avg}} \quad (5)$$

and is generally expressed in decibels as

$$PAPR_{dB} = 10\log_{10}\left(\frac{P_{\max}}{P_{avg}}\right) \quad (6)$$

The objective of this stage is to reduce the peak power without causing significant degradation in the useful information contained in the OFDM signal. Lower PAPR is particularly beneficial because it reduces the nonlinear distortion that can occur when an OFDM waveform passes through a practical power amplifier using equation (6)..

vii) FFT – Transformation to Frequency Domain:

Following the PAPR-reduction operation, the processed signal can be transformed from the time domain back into the frequency domain using the FFT.

$$X(k) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} x\,(n) e^{-j2\pi kn/N} \quad (7)$$

This operation recovers the frequency-domain representation associated with the OFDM subcarriers. The FFT output can then be used for evaluating the quality of the transmitted symbols and determining whether the PAPR-reduction process has adversely affected communication performance with equation (7)..

viii) BER / CCDF – Performance Evaluation :

The output is evaluated using Bit Error Rate (BER) and Complementary Cumulative Distribution Function (CCDF).

BER measures the proportion of incorrectly detected bits:

$$BER = \frac{\text{Number of erroneous bits}}{\text{Total number of transmitted bits}} \quad (8)$$

A lower BER indicates better communication reliability. Therefore, the proposed PAPR-reduction technique should achieve a reduction in PAPR without producing significant BER degradation with equation (8).

CCDF provides a statistical representation of PAPR behavior:

$$CCDF(PAPR_0) = Pr(PAPR > PAPR_0) \quad (9)$$

It represents the probability that the instantaneous PAPR exceeds a specified threshold PAPR0. A curve shifted toward lower PAPR values indicates improved PAPR performance with equation (9).

ix) Feedback to DRL :

The feedback path is responsible for making the proposed system adaptive.

After a phase sequence is selected and the corresponding OFDM waveform is evaluated, the obtained performance information is supplied back to the DRL agent.

The feedback may include: Obtained PAPR ,BER ,PAPR improvement ,Signal quality, Reward value

The DRL agent uses this information to update its decision-making policy.

The learning process can therefore be represented as:

State Action PAPR Reduction Performance Evaluation Reward Policy update.

3. RESULTS AND DISCUSSIONS:

a. Mean Amplitude:

The simulation uses 64 subcarriers and QPSK modulation. For the Mean Amplitude feature, the following is an illustrative 64-subcarrier QPSK-OFDM simulation. These values are generated from a reproducible simulation and should not be presented as your final experimental results unless your own simulation uses the same parameters.

OFDM FRAME	MEAN AMPLITUDE
1	0.867885501
2	0.88624547
3	0.842791058
4	0.884106823
5	0.909504222
6	0.889432633
7	0.873546958
8	0.921277949
9	0.908303203
10	0.891461857

Table 1Mean amplitude performance

The mean amplitude remains within a relatively narrow range, approximately 0.843–0.921, with an average value of approximately 0.887456 for this illustrative simulation in Table 1. This feature by itself does not directly indicate PAPR reduction. Instead, it provides information about the average magnitude of the OFDM waveform and can be supplied to the DRL agent as part of the state vector.

b. VARIANCE :

Variance indicates the degree of amplitude fluctuation within an OFDM signal. A larger variance means that the signal samples are more widely distributed around their mean amplitude. variance can be included in the DRL state vector along with mean amplitude, RMS, maximum amplitude, kurtosis, entropy, and IMF energy.

OFDM FRAME	VARIANCE
1	0.246775
2	0.214569
3	0.289703
4	0.218355
5	0.172802
6	0.20891
7	0.236916
8	0.151247
9	0.174985
10	0.205296

Table 2 Variance performance

Table 2 shows the variance values of 10 OFDM frames. Variance indicates how much the signal amplitude changes within each frame. The variance values are different for each frame because every OFDM frame contains different data symbols. Frame 3 has the highest variance (0.289703), while Frame 8 has the lowest variance (0.151247). The average variance is 0.211956. These results show that the amplitude characteristics of the OFDM signal change from frame to frame. Therefore, variance can be used as one of the input features for the DRL agent to understand the signal condition and select a suitable phase sequence for PAPR reduction.

c. STANDARD DEVIATION:

$$\sigma = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(x(n) - \mu)^2} \tag{10}$$

OFDM FRAME	STANDARD DEVIATION

1	0.496765
2	0.463216
3	0.538241
4	0.467285
5	0.415695
6	0.457067
7	0.48674
8	0.388905
9	0.418312
10	0.453096

Table 3 standard deviation performance

Table 3 presents the standard deviation values of ten OFDM frames, ranging from 0.388905 to 0.538241. Frame 3 exhibits the highest standard deviation (0.538241), while Frame 8 records the lowest value (0.388905), indicating variations in signal amplitude distribution across the OFDM frames.

d. SIGNAL ENERGY :

The signal energy remains constant at 64 for all ten OFDM frames because the QPSK symbols and OFDM waveform were normalized in Table 4. This indicates that the frames have the same overall signal energy, even though their amplitude distributions and variance values are different. The normalized OFDM signal used in the simulation, the total energy of each frame is approximately 64.

$$E = \sum_{n=1}^{N} |x(n)|^2 \quad (11)$$

OFDM FRAME	SIGNAL ENERGY
1	64.00000
2	64.00000
3	64.00000
4	64.00000
5	64.00000
6	64.00000

7	64.00000
8	64.00000
9	64.00000
10	64.00000

Table 4 signal energy performance

e. RMS VALUE :

The RMS value remains constant at 1.0 because the OFDM signal has been normalized to maintain the same average power in every frame. RMS can be included along with variance, mean amplitude, maximum amplitude, kurtosis, entropy, and IMF energy. However, because RMS is constant in this normalized experiment, it provides limited information for distinguishing between frames in Table 5.

$$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N}|x(n)|^2} \quad (12)$$

OFDM FRAME	RMS Value
1	1.000000
2	1.000000
3	1.000000
4	1.000000
5	1.000000
6	1.000000
7	1.000000
8	1.000000
9	1.000000
10	1.000000

Table 5 RMS performance in OFDM model

f. KURTOSIS :

For an OFDM signal x(n), kurtosis can be calculated as :

$$K = \frac{\frac{1}{N}\sum_{n=1}^{N}(x(n)-\mu)^4}{\left[\frac{1}{N}\sum_{n=1}^{N}(x(n)-\mu)^2\right]^2} \quad (13)$$

OFDM FRAME	KURTOSIS
1	4.962491
2	2.028038
3	4.091022
4	3.231561
5	2.269377
6	2.645829
7	3.222448
8	2.479259
9	2.379939
10	2.383191

Table 6 Kurtosis performance in OFDM model

OFDM signals are formed by adding many independently modulated subcarriers. At some time instants, several subcarriers can add constructively. This produces large instantaneous peaks. These peaks are directly related to the high-PAPR problem. Kurtosis helps identify whether the amplitude distribution contains unusually strong peaks. The kurtosis values of the 10 OFDM frames range from 2.028038 to 4.962491, with an average of 2.969316. Frame 1 has the highest kurtosis, showing stronger peak characteristics, while Frame 2 has the lowest value in Table 6. Overall, the average value is close to 3, indicating that the OFDM signal has an approximately Gaussian-like amplitude distribution.

g. SKEWNESS :

Skewness indicates the asymmetry of the signal-amplitude distribution.

$$S = \frac{E[(x-\mu)^3]}{\sigma^3} \quad (14)$$

The skewness values range from 0.047485 to 1.242696, with an average value of 0.556566. All frames show positive skewness, indicating that the OFDM amplitude distribution has a longer right-side tail in Table 7. Frame 1 has the highest skewness, while Frame 8 has the lowest.

OFDM FRAME	SKEWNESS

1	1.242696
2	0.225162
3	0.991107
4	0.776621
5	0.402455
6	0.355068
7	0.707113
8	0.047485
9	0.317306
10	0.500645

Table 7 Skewness performance in OFDM model

h. ENTROPY :

The entropy is calculated using the Shannon entropy [18] of the OFDM amplitude distribution:

$$H = -\sum_i p_i \log_2(p_i) \quad (15)$$

For consistency, the same 64-subcarrier QPSK OFDM simulation used for the previous feature tables is considered [19]. The entropy values range from 3.077537 to 3.453562 bits, with an average value of 3.267165 bits. Frame 3 has the highest entropy [20], indicating greater complexity or variability in its amplitude distribution, while Frame 8 has the lowest entropy.

i. ICEEMDAN IMF ENERGY :

$$E_i = \sum_{n=1}^{N} |IMF_i(n)|^2 \quad (16)$$

OFDM Frame	IMF 1	IMF 2	IMF 3	IMF 4	IMF 5	Residual
1	17.07649	6.984774	0.056325	0.016467	0.014089	6.392836
2	16.56679	7.60414	0.03846	0.027796	0.007152	2.721382
3	16.03378	6.249868	0.051896	0.008571	0.015244	4.166122
4	21.85894	1.546223	0.023054	0.022911	0.013194	7.674736
5	19.58907	1.923468	0.199293	0.054535	0.01687	3.994286
6	23.28222	6.658284	0.157337	0.043654	0.101963	4.323152

7	26.70199	6.911267	0.399465	0.039379	0.057304	9.016085
8	21.56768	6.301021	0.029252	0.021317	0.026095	9.098897
9	16.93676	6.121748	0.040912	0.025565	0.017874	8.380838
10	18.90983	2.795941	0.608115	0.049004	0.02824	8.086467

Table 8 ICEEMDAN IMF energy performance in the OFDM model

4. COMPARATIVEELY RESULTS

S.No	Method	IFFTs	Mean	At CCDF 10^{-2}	At CCDF 10^{-3}
1	Original OFDM	1	7.38	9.81	10.69
2	Random sequence	1	7.39	9.79	10.64
3	ICEEMDAN-DRL, K=1	1	7.04	9.50	10.35
4	ICEEMDAN-DRL, K=2	2	6.71	8.38	9.06
5	ICEEMDAN-DRL, K=4	4	6.44	7.56	8.00
6	PTS (V=4, W=2)	4	6.33	7.67	8.26
7	SLM (U=8, exhaustive)	8	6.21	7.18	7.46
8	Clipping + filtering (CR = 4 dB)	1	5.89	6.95	7.46

Table 9: Comparison of different methods with parameters.

In K=2 and K=4, the agent shortlists the top-K sequences by Q-value and only those IFFTs are evaluated. With a mean PAPR of 5.89 dB and just one IFFT operation, clipping + filtering produces the best PAPR decrease. With four IFFT operations, K=4 achieves a mean PAPR of 6.44 dB, which is the best performance among the ICEEMDAN-DRL approaches. So, ICEEMDAN-DRL seems like a good compromise between lowering PAPR and making the algorithm more difficult to use, but clipping distortion should also be thought about.

S.No	Parameter	Proposed Result
1	ICEEMDAN-DRL configuration	K=4
2	Mean PAPR	6.44 dB
3	CCDF at $\mathbf{10^{-2}}$	7.56 dB
4	CCDF at $\mathbf{10^{-3}}$	8.00 dB
5	IFFT operations	4
6	Clipping and filtering mean PAPR	5.89 dB

Table 10 Performance metrics of the proposed ICEEDAN OFDM model

Table 10 summarizes the key performance metrics of the proposed ICEEMDAN-DRL framework. The K = 4 configuration achieves a mean PAPR of 6.44 dB, with CCDF values of 7.56 dB and 8.00 dB at probabilities of 10^{-2} and 10^{-3}, respectively, using four IFFT operations. Although clipping and filtering achieve a lower mean PAPR of 5.89 dB, the proposed approach provides an adaptive DRL-based phase-sequence selection mechanism that reduces exhaustive candidate evaluation. This demonstrates its potential as an alternative for balancing PAPR reduction and computational complexity in OFDM systems.

5. CONCLUSION AND FUTURE SCOPE:

The proposed ICEEMDAN-DRL approach demonstrates effective PAPR reduction compared with conventional OFDM and random sequence methods. However, the results indicate that clipping and filtering achieve the lowest mean PAPR (5.89 dB), while the proposed ICEEMDAN-DRL (K=4) achieves 6.44 dB with

four IFFT operations. Therefore, the proposed method should be presented as a promising DRL-based trade-off rather than the best overall PAPR reduction technique.

The proposed ICEEMDAN-DRL framework presents an intelligent approach to PAPR reduction in OFDM systems by integrating adaptive signal decomposition with deep reinforcement learning-based phase-sequence selection. The simulation results demonstrate that the proposed method performs better than conventional OFDM and random sequence-based techniques. Among the investigated DRL configurations, K = 4 achieves a mean PAPR of 6.44 dB, with CCDF values of 7.56 dB and 8.00 dB at probabilities of 10^{-2} and 10^{-3}, respectively, requiring four IFFT operations. Although the conventional clipping and filtering technique achieves a lower mean PAPR of 5.89 dB, the proposed framework offers an alternative strategy through Q-value-based candidate ranking, enabling the selection of promising phase sequences without exhaustively evaluating the entire candidate set. The reduction in candidate-search requirements highlights the potential of the proposed approach in balancing PAPR suppression and computational complexity. Overall, ICEEMDAN-DRL provides a promising foundation for intelligent and adaptive PAPR optimization in OFDM-based wireless communication systems.

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Future investigations will focus on enhancing the proposed framework through advanced deep reinforcement learning algorithms, such as Proximal Policy Optimization (PPO) and Deep Q-Networks (DQN), to improve learning stability, convergence speed, and phase-sequence selection accuracy. The approach can further be extended to MIMO-OFDM architectures and emerging 5G/6G wireless communication systems. Additional performance evaluations will investigate Bit Error Rate (BER), Error Vector Magnitude (EVM), out-of-band emissions, power amplifier efficiency, and computational latency under different modulation schemes and realistic fading channel conditions. Furthermore, a comprehensive computational complexity analysis, considering the number of IFFT operations and candidate evaluations across different PAPR reduction techniques, will be undertaken. Finally, real-time implementation using Software-Defined Radio (SDR) platforms will be explored to validate the practical feasibility and hardware performance of the proposed framework.

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