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Research Article

A Comprehensive Review on OFDM, 5G and Various PAPR Minimization Techniques based on Machine Learning

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ABSTRACT

The use of modulation methods in Fifth Generation (5G) wireless communication systems is essential for fulfilling the requirements of increased data rates, reduced latency, and enhanced connection. This entails the optimization of power spectral density (PSD), the improvement of data transmission reliability, and the reduction of bit error rates (BER) and interference. Orthogonal Frequency Division Multiplexing (OFDM) is the modulation technique used in 4G and 5G wireless communication networks. OFDM results in a significant Peak to Average Power Ratio (PAPR) in the time domain because of the constructive interference between many subcarriers. This leads to increased complexity and expense of amplifiers, as well as higher costs and complexity of networks. Hence, it is essential to devise novel approaches to mitigate the PAPR in OFDM systems. ML has become a potential approach for addressing PAPR concerns. This study provides a thorough examination of ways for optimizing PAPR, with a specific emphasis on ML approaches.

1. INTRODUCTION

The domain of wireless communication has had a deep and transformational evolution, significantly altering our connectedness and interactions. Wireless technology has enabled effortless transfer of data across the airways, surpassing the limitations of wired networks, from its creation till its widespread use today [1]. The widespread availability, extensive communication capabilities, and prevalence of mobile devices have profoundly transformed our interaction with information and one another on a worldwide scale. Modulation is the fundamental principle of wireless communication, allowing information to be encoded into carrier signals for wireless transmission. Modulation is a technique used to modify parameters like as amplitude, frequency, or phase of the carrier signal. This manipulation helps in the efficient and reliable transmission of data across the wireless medium. It is essential for the encryption and decryption of vital information required for the wireless transmission of audio, video, and data [2].

Mobile communication plays a crucial function in contemporary life. Over the last several years, there has been a significant surge in the availability of communication services, video conferencing, online gaming, e-education, video on demand, and other such services that need higher and higher data speeds. New mobile generations have emerged almost every decade from the first transition from analog (1G) in 1981, which enabled voice transmission, to digital (2G) transmission in 1992, which offered improved system capacity and quality of service (QoS). In 2001, 3G cellular networks offered internet connectivity, fast data transfer speeds, support for multimedia, and wide spectrum transmission. The need for smartphones with huge storage capacity, high processing capabilities, high-definition screens, and advanced cameras led to the development of 4G technology in 2011. Throughout the evolution of mobile communication, there has been a strong focus on enhancing data transmission speeds. The incessant demands for increased data speeds, reduced latency, improved cost effectiveness, and enhanced capacity have led to anticipated scenarios for the 5G technology. OFDM is the method used in 4G [3]. It is a commonly used technology because it is very resistant to interference caused by signals bouncing off obstacles. The employment of a lengthy symbol duration and cyclic prefix in OFDM base signals, such as LTE, leads to a reduction in spectral efficiency. The spectrum in LTE is determined by the transition between successive OFDM symbols, which in turn leads to the generation of out-of-band emissions (OOB)[4]. The limitations and problems of OFDM have shaped the

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development of 5G waveforms [5]. In addition, there was a need for reduced latency to meet the demands of high-demand applications such as autonomous driving and highly robust communication links.

OFDM is the modulation technology used in 4G and 5G wireless systems and is anticipated to continue being essential in order to fulfill the demanding requirements of 6G networks [6-10]. Networks, unlike previous generations, function at higher frequencies and wider bandwidths. This poses unique obstacles for implementing OFDM, specifically with concerns such as high PAPRand Inter-Carrier Interference (ICI), as described in [11]. Furthermore, OFDM is well recognized for its capability to manage frequency selective fading, optimize spectrum use, and withstand interference [12]. Nevertheless, it encounters challenges as a result of the compact arrangement of the subcarriers that are inherent in its design, resulting in a significant PAPR. This heightened PAPR has many consequences. Initially, it might lead to intermodulation distortion, which causes a decline in the quality of the signal being broadcast. Furthermore, it reduces the effectiveness of the amplifiers used in the system, as they need to adjust to the elevated peaks by functioning within a wider range of variability. Ultimately, a high PAPR might result in the emission of undesired signals into adjacent frequency bands, leading to interference with other wireless systems [13-14]. When a high PAPR is not properly controlled, it is necessary to use sophisticated techniques in signal processing and amplifier designs. However, these techniques may result in significant delays in the transmission and reception of signals. These delays may result in heightened latency, which is unfavorable in networks that aim for ultralow-latency communication [15-18]. Therefore, it is essential to optimize the PAPR in order to minimize interference, achieve high spectral efficiency, reduce distortion, and get low-latency signals in network contexts [19].

The study outlines a methodical approach to understanding several techniques that tackle the issue of high PAPR in OFDM systems. It is a very important resource for new researchers who are looking for a thorough knowledge of the PAPR. Nevertheless, the methodologies examined in [20] for mitigating PAPR in wireless communication systems may not adequately tackle the intricate and ever-changing nature of the issue. Traditional methods often depend on predetermined signal processing techniques and parameter settings that may not adequately adjust to the changing circumstances of wireless channels. Although these solutions may provide a certain level of decrease in PAPR, they may not possess the flexibility needed to constantly maintain excellent signal quality in the presence of varying communication situations. Hence, the authors of [20] recognized the importance of traditional methods, but they specifically avoided discussing machine learning approaches for reducing PAPR.

2. 5G TECHNOLOGY

5G is the next generation of cellular mobile communications, after the 4G, 3G, and 2G systems. It offers groundbreaking features and advancements. 5G technology is the next iteration of mobile networking standards, aiming to enhance the end-user experience by providing new apps and services via uninterrupted coverage, a rapid data transfer rate, minimal delay, substantially enhanced performance, and dependable communication [21-22]. 5G technology will enhance energy efficiency, spectrum efficiency, network efficiency, and the efficiency of other systems.

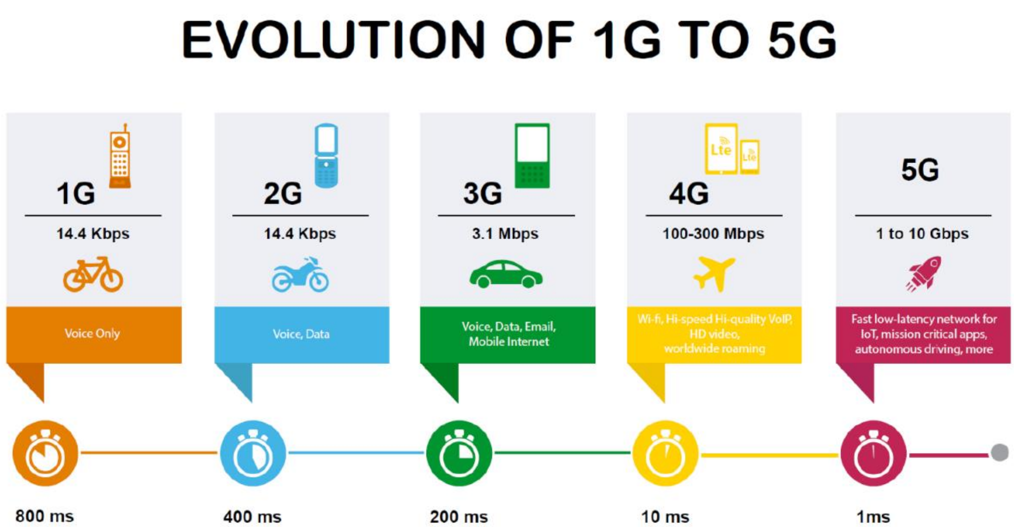

Fig. 1. Evolution from 1G to 5G Technology

Technology	1G	2G	3G	4G	5G
Deployment	1970/ 1984	1980/1999	1990/2002	2000/2010	2014/2015
Bandwidth	2kbps	14-64kbps	2mbps	200 mbps	>1 gbps
Technology	Analog cellular	Digital cellular	Broad Bandwidth / CDMA / ip technology	Unified IP & seamless combo of LAN/ WAN/ WLAN/ PAN	4G+ WWW
Service	Mobile telephony	Digital voice, short messaging	Integrated high-quality audio, video & data	Dynamic information access, variable devices	Dynamic information access, variable devices with AI capabilities
Multiplexing	FDMA	TDMA/CDMA	CDMA	CDMA	CDMA
Switching	Circuit	Circuit / circuit for access network & air interface	Packet except for air interface	All packet	All packet
Core network	PSTN	PSTN	Packet network	Internet	Internet
Handoff	Horizontal	Horizontal	Horizontal	Horizontal & vertical	Horizontal & vertical

Fig. 2. Comparison of 1G to 5G [23-25]

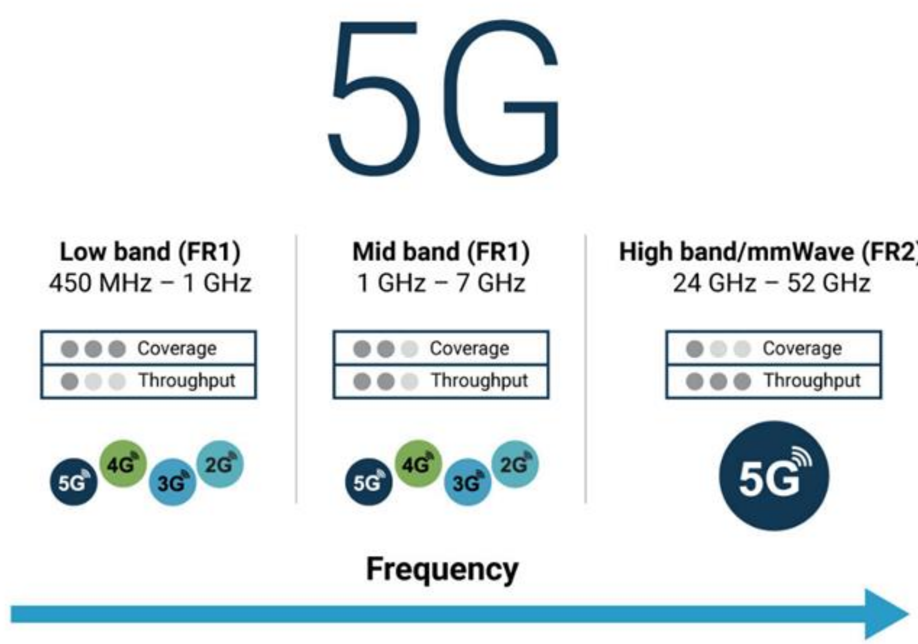

Fig. 3. Different Bands of 5G

2.1 Advantages of 5G Technology

5G technology is presented as the next wireless technology that develops upon previous versions, bringing about a significant change and opening up new opportunities for many businesses and customers [23-25]. The 5G technology has many beneficial characteristics:

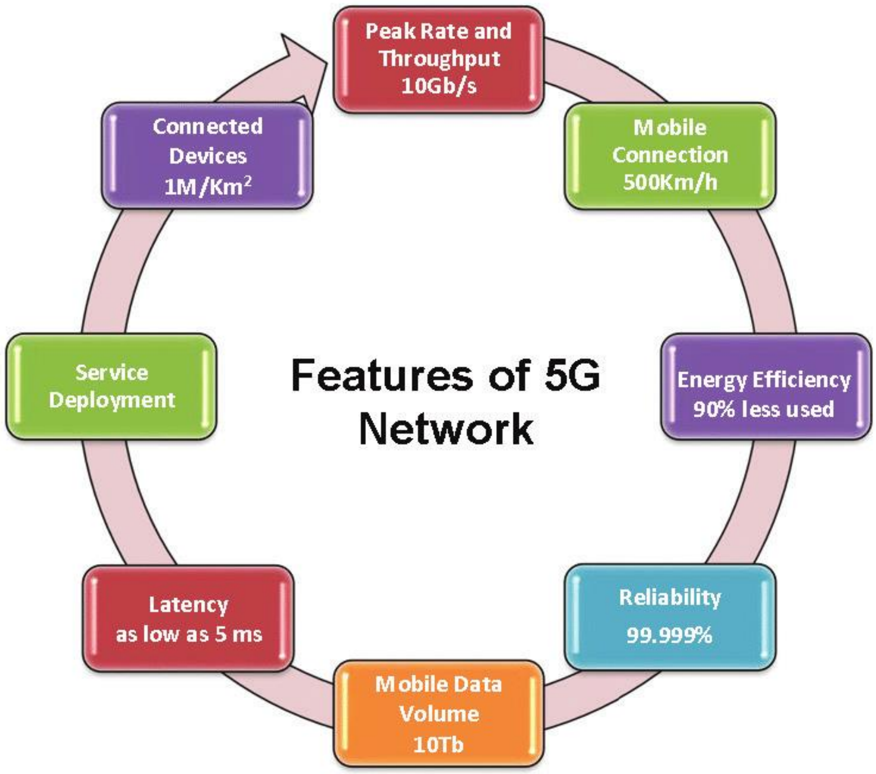

Fig. 4. Features of 5G

- **Increased Connectivity**: 5G technology is expected to deliver faster and more reliable internet connectivity, facilitating more devices to connect to the internet and enabling new technologies and applications to operate with lower latency.
- **Enhanced Experiences**: 5G is expected to offer new and improved experiences in virtual and augmented reality, gaming, and video streaming.
- **Enabling Real-Time Collaboration**: People will be able to interact and collaborate in real-time in virtual environments via 5G technology, which will eliminate the delays and lag that are currently experienced on slower networks.
- **Supporting High-Quality Content**: 5G technology is enabling the creation and delivery of high-quality content such as 3D graphics.
- **Enabling new applications and services**: 5G technology is expected to enable new metaverse applications and services such as virtual education, virtual healthcare, and virtual tourism.

2.2 Limitations of 5G Technology

5G technology has the potential to improve enterprise operations and the competitiveness of the digital economy. However, there are also some negative aspects to consider, including the following:

- **High infrastructure cost:** 5G service is likely to be more expensive, at least initially, because the deployment of 5G networks requires significant investment in infrastructure and its improved features may also be reflected in the price of 5G service.
- **Security Risks**: 5G networks, like any new technology, may be vulnerable to security threats such as hacking and cyberattacks.
- **Privacy Concerns**: Concerns about personal privacy may arise as a result of the increased use of data and connected devices enabled by 5G technology.

- **Device Compatibility**: The transition to 5G necessitates compatible devices, with newer models supporting it. Older devices may not work with 5G, causing a fragmented user experience. This rollout may worsen economic and social inequalities by unevenly distributing access to technology.
- **Health Concerns**: There are concerns about the potential health consequences of 5G, such as increased exposure to radiofrequency (RF) radiation. However, the World Health Organization has determined that the levels of RF radiation emitted by 5G technology are safe.

2.3 Applications of 5G Technology

5G Technology will enable wireless service providers to develop innovative business models, benefiting various sectors like industrial, commercial, educational, healthcare, agriculture, etc.

- **Health Sector**: 5G technology can facilitate high-quality telemedicine services, allowing for remote consultations, real-time monitoring of patients, and tele-treatment where doctors can treat patients while maintaining social distancing norms like those required during COVID-19.
- **Internet of Things (IoT)**: 5G's promise of low latency and high network capacity helps to eliminate the biggest limitations to IoT expansion [26-29] .
- **Augmented and Virtual Reality**: 5G backhaul enables data speeds that are several times faster than 4G, ensuring real-time and uninterrupted AR/VR experiences.
- **Agriculture**: Using data from sensors installed directly in fields, farmers can pinpoint which areas require water, have a disease, or require pest management.
- **Manufacturing**: Factories will also use 5G to control and analyze industrial processes with an unprecedented degree of precision. 5G offers unimaginable possibilities to power Industry 4.0, from video monitoring to fixed wireless access, immersive experiences and smart stadiums toe-health, machine remote control, cloud robotics, process automation, and assisted/autonomous vehicles.
- **Logistics**: Inventory tracking is costly, slow, and difficult in shipping and logistics. 5G has the potential to improve vehicle-to-vehicle communication as well as vehicle-to-infrastructure communication. Fleet monitoring and navigation will become significantly easier at scale with 5G.

3. ORTHOGONAL FREQUENCY DIVISION MULTIPLEXING (OFDM)

OFDM is a digital modulation technique widely used in modern wireless communication systems, including LTE, Wi-Fi, and 5G. OFDM is a cornerstone of modern wireless communication, offering significant advantages in terms of spectral efficiency and robustness, but it comes with challenges such as high PAPR and the need for precise synchronization. Frequency Division Multiplexing (FDM) and OFDM are important methods used in modern wireless communication systems [30-31]. They have a long history and are widely used due to their practical value. Their evolution has been propelled by the urgent need to surmount many obstacles linked to wireless data transmission, including as interference, fading, and the limitation of bandwidth. These technologies are fundamental to many communication standards and are anticipated to remain essential in the development of wireless communication systems.

In the frequency domain, the OFDM signal consists of multiple closely spaced subcarriers. Each subcarrier is modulated with data, and the resulting spectrum is a sum of these individual subcarriers. Each subcarrier has a sinc (sin(x)/x) shape in the frequency domain, with its main lobe containing the majority of the signal energy and side lobes gradually decaying. Although the subcarriers overlap in the frequency domain, their orthogonality ensures that there is no interference between them at the sampling points, where the signal is decoded. OFDM's ability to use overlapping subcarriers without interference results in high spectral efficiency, which means that it can transmit more data within a given bandwidth compared to traditional single-carrier systems. OFDM allows for adaptive modulation, where different subcarriers can be modulated differently based on channel conditions. This further enhances the efficiency and robustness of the system [32-34]. To combat ISI caused by multipath propagation, a cyclic prefix is added to each OFDM symbol. This cyclic prefix extends the duration of the OFDM symbol, slightly reducing the overall spectral efficiency but improving robustness in multipath environments. Sometimes, small frequency gaps called guard bands are placed at the edges of the OFDM spectrum to prevent interference with adjacent channels or systems. These guard bands help maintain the integrity of the transmitted signal. The PSD of an OFDM signal is relatively flat across the subcarriers, indicating uniform power distribution across the used bandwidth. This is ideal for maximizing the use of available spectrum. A notable characteristic of OFDM is its high PAPR, which means that the OFDM signal can have large peaks relative to its average power. This requires careful design of amplifiers and power management techniques to handle these peaks without distortion. OFDM is sensitive to frequency offsets and Doppler shifts, which can cause subcarriers to lose orthogonality, leading to ICI. This necessitates precise frequency synchronization in OFDM systems [35].

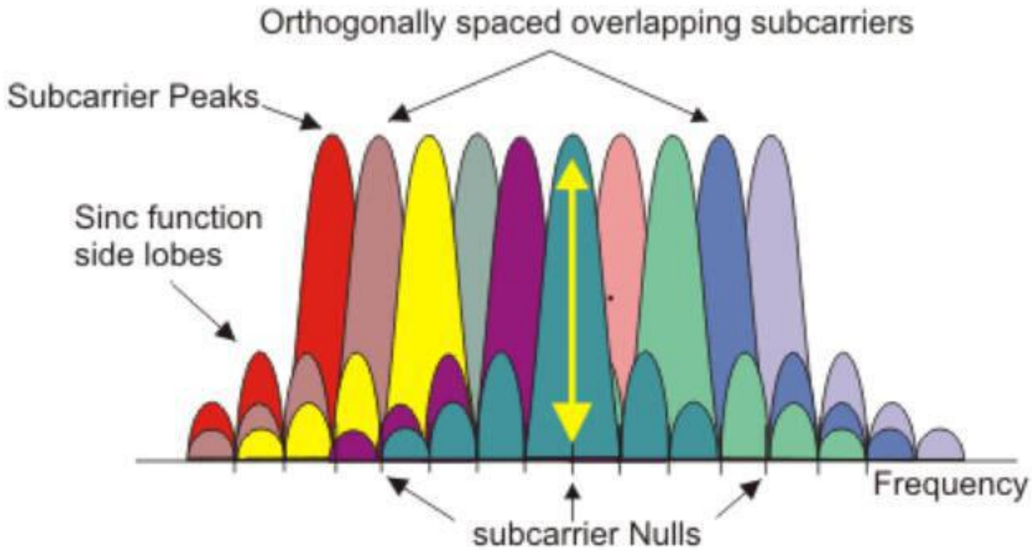

Fig. 5. OFDM signal frequency Spectrum

3.1 Block Diagram of OFDM

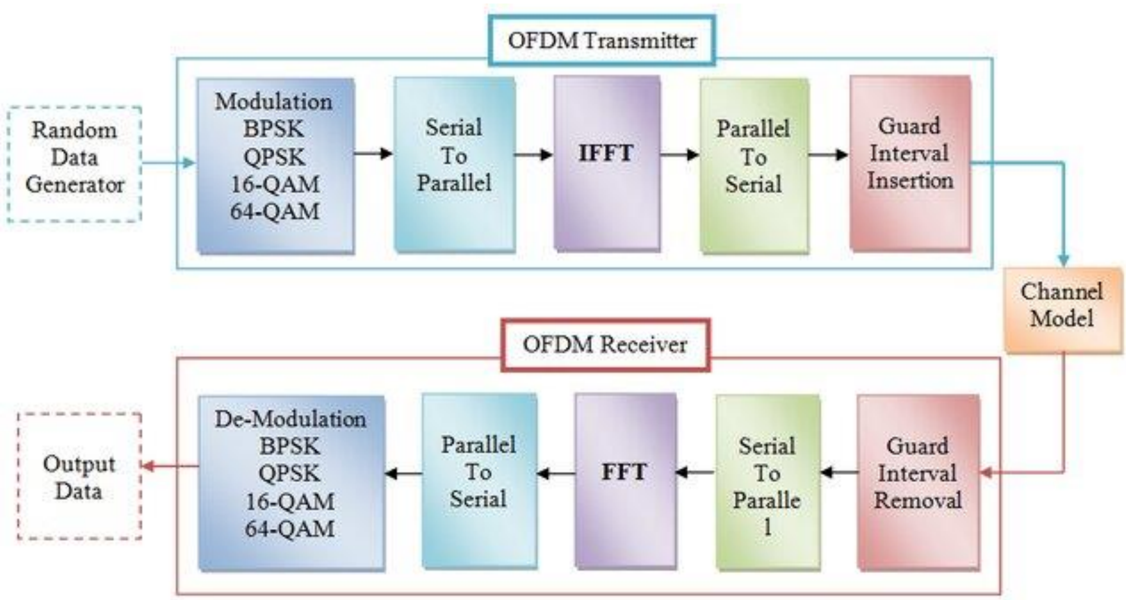

Fig. 6. OFDM - Block Diagram

- **Input Data**: The input data stream is divided into multiple parallel data streams, each of which will modulate a different carrier frequency.
- **Modulation**: Each data stream is modulated using a digital modulation scheme like QAM (Quadrature Amplitude Modulation) or PSK (Phase Shift Keying).
- **IFFT**: The modulated symbols are fed into an IFFT block, which converts the frequency domain data into the time domain. This ensures that the subcarriers are orthogonal to each other.

- **Cyclic Prefix (CP) Insertion**: A cyclic prefix is added to each OFDM symbol to prevent ISI and maintain orthogonality in multipath environments.
- **Parallel-to-Serial Conversion**: The parallel data streams are converted back to a single serial data stream.
- **Transmission**: The serial data stream is transmitted over the communication channel.
- **Receiver (Reverse Process):** The receiver performs the reverse operations: cyclic prefix removal, FFT to convert back to the frequency domain, demodulation, and parallel-to-serial conversion to recover the original data.
- **Parallel Data Transmission**: OFDM splits the data into multiple parallel streams, which are transmitted simultaneously over different orthogonal subcarriers. This increases the efficiency of the spectrum.
- **Orthogonality**: The subcarriers are carefully spaced to be orthogonal, meaning they don't interfere with each other despite overlapping in the frequency domain.
- **Cyclic Prefix**: Adding a cyclic prefix to each symbol prevents ISI and preserves orthogonality in the presence of multipath propagation.

3.2 Advantages of OFDM

- **Spectral Efficiency**: High spectral efficiency due to the use of closely spaced orthogonal subcarriers.
- **Robustness to Multipath Fading**: The cyclic prefix and orthogonality make OFDM highly resistant to multipath fading, which is common in wireless communication.
- **Scalability**: OFDM can easily scale to different bandwidths and transmission rates, making it suitable for various applications.
- **Efficient Use of Bandwidth**: The overlapping nature of subcarriers allows for more efficient use of the available bandwidth.

3.3 Disadvantages of OFDM

- **High PAPR**: OFDM signals can have high PAPR, requiring linear amplifiers with a large dynamic range, leading to inefficiency in power consumption.
- **Synchronization Issues**: Accurate synchronization is required to maintain the orthogonality of the subcarriers, which can be challenging in practice.
- **Complexity**: The implementation of OFDM requires complex digital signal processing, particularly in terms of FFT/IFFT operations.
- **Sensitivity to Frequency Offset**: OFDM systems are sensitive to frequency offsets and Doppler shifts, which can cause ICI.

3.4 Key Characteristics of OFDM

- **Orthogonality:** The core principle that allows subcarriers to overlap without interference.
- **Cyclic Prefix**: A critical component for maintaining symbol integrity in multipath environments.
- **High Data Rates**: Capable of supporting high data rates due to parallel data transmission.
- **Scalability**: Flexibility in adapting to different bandwidths and channel conditions.

4. PAPR MINIMIZATION METHODS

PAPR is a critical metric in communication systems, particularly in OFDM. It is the ratio of the peak power of a signal to its average power. High PAPR indicates that the signal has a few large peaks relative to its average level, which can cause problems in power amplification and signal distortion. Each method for reducing PAPR in OFDM systems has its trade-offs between complexity, effectiveness, and impact on system performance [36-37]. The choice of method depends on the specific requirements of the system, such as the allowable complexity, tolerance for signal distortion, and the importance of maintaining data rate and power efficiency. High PAPR requires power amplifiers with a large dynamic range to avoid signal clipping and distortion, leading to inefficiency and higher power consumption.

PAPR is defined as, PAPR = Peak Power / Average Power

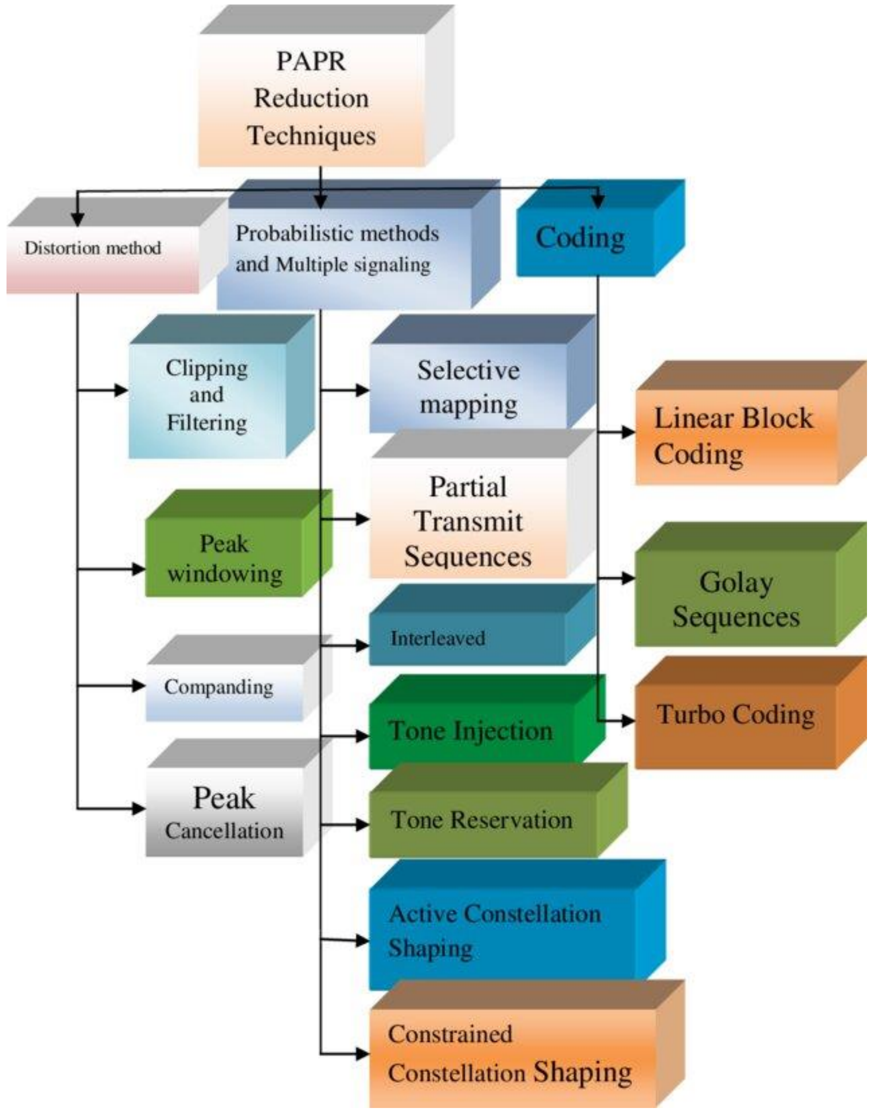

Fig. 7. Various PAPR minimization methods [36]

TABLE I. COMPARISON OF VARIOUS PAPR MINIMIZATION METHODS [36]

Method	**Description**	**Merits**	**Demerits**
Clipping and Filtering	The simplest method where the signal is clipped at a predefined level, reducing peaks, followed by filtering to reduce out-of-band radiation.	Simple and easy to implement. Significant reduction in PAPR.	Causes in-band distortion and out-of-band radiation. May degrade Bit Error Rate (BER) performance.
Selective Mapping (SLM)	Multiple versions of the same OFDM signal are generated by multiplying the data block with different phase sequences, and the one with the lowest PAPR is selected for transmission [37].	Effective in reducing PAPR without distorting the signal. No in-band distortion.	Requires additional signaling to inform the receiver about the phase sequence used. Increased computational complexity.
Partial Transmit Sequence (PTS)	The input data block is divided into sub-blocks, each of which is multiplied by a phase factor. The phase factors are chosen to minimize the PAPR [32-33].	Significant PAPR reduction without signal distortion.	Increased computational complexity. Requires side information to be sent to the receiver.
Tone Reservation	A small number of subcarriers (tones) are reserved for PAPR reduction. These tones do not carry data but are used to shape the signal in such a way that reduces peaks.	No in-band distortion. Relatively simple implementation.	Reduces the data rate as some subcarriers are reserved. Less effective if few tones are reserved.

Tone Injection	Similar to tone reservation, but instead of reserving subcarriers, additional signals are added to subcarriers carrying data to reduce peaks.	Effective PAPR reduction without additional signaling	Requires more transmit power. Increased complexity in signal generation.
Coding Techniques	Special codes are used to encode the data in such a way that the resulting OFDM signal has a lower PAPR.	No distortion introduced. Can achieve significant PAPR reduction.	Reduces coding efficiency, leading to lower data rates. Increased complexity in coding and decoding.
Interleaving	Data is interleaved before modulation, leading to different sequences that result in different PAPR values. The sequence with the lowest PAPR is selected.	Simple and effective for reducing PAPR. No additional side information required.	May require multiple IFFT operations, increasing computational load. Limited PAPR reduction.

TABLE II. COMPARISON OF VARIOUS PAPR MINIMIZATION METHODS

Method	**PAPR Reduction**	**Complexity**	**Signal Distortion**	**Impact on BER**	**Side Information**
Clipping and Filtering	Moderate	Low	High	Degrades	No
SLM	Moderate	Moderate to high	None	No impact	Yes
PTS	significant	High	None	No impact	Yes
Tone Reservation	Moderate to good	Low to moderate	None	No impact	Yes
Tone Injection	significant	Moderate	None	No impact	No
Coding Techniques	Moderate to significant	High	None	Can improve or degrade	No
Interleaving	Moderate	Low to moderate	None	No impact	Yes

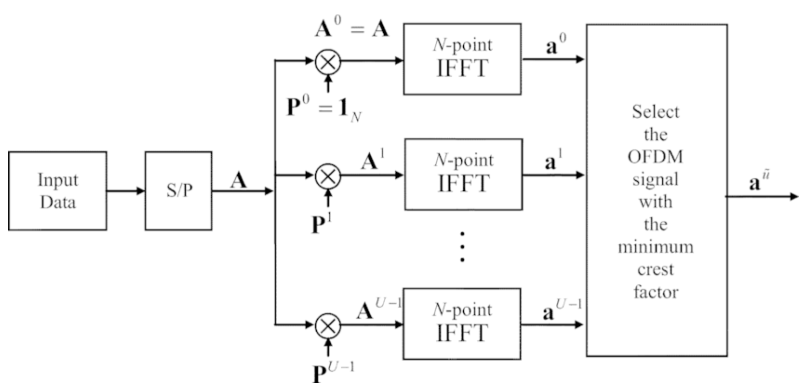

Fig. 8. Block diagram of the SLM OFDM scheme [38]

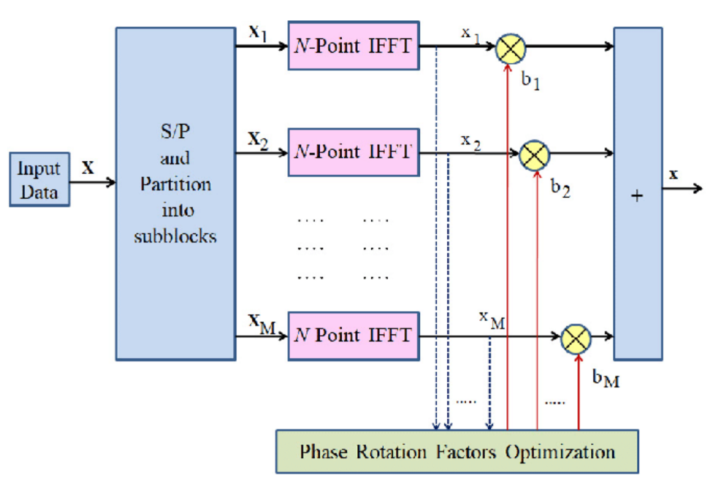

Fig. 9. Block diagram of the PTS OFDM [39]

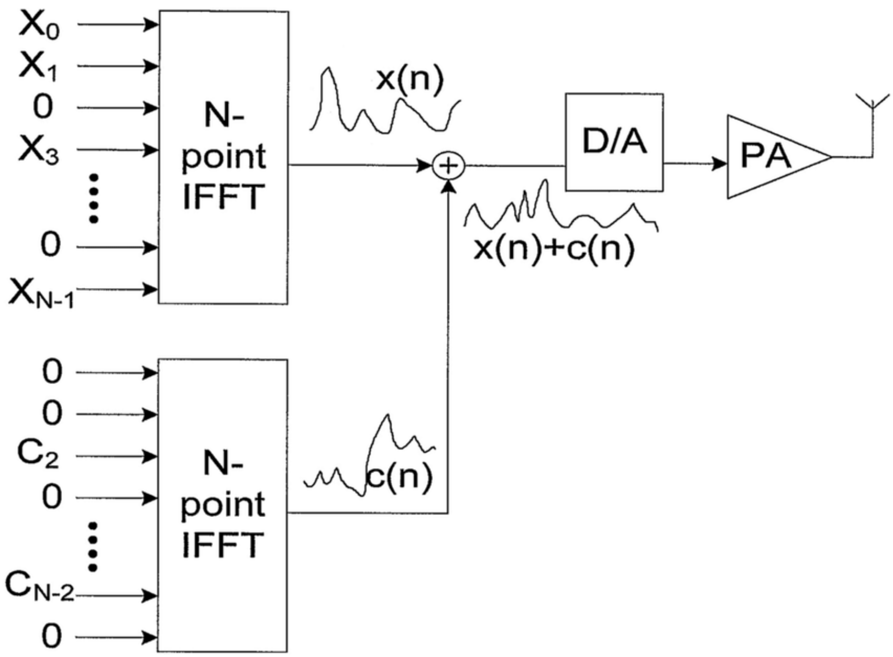

Fig. 10. OFDM transmitter for TR

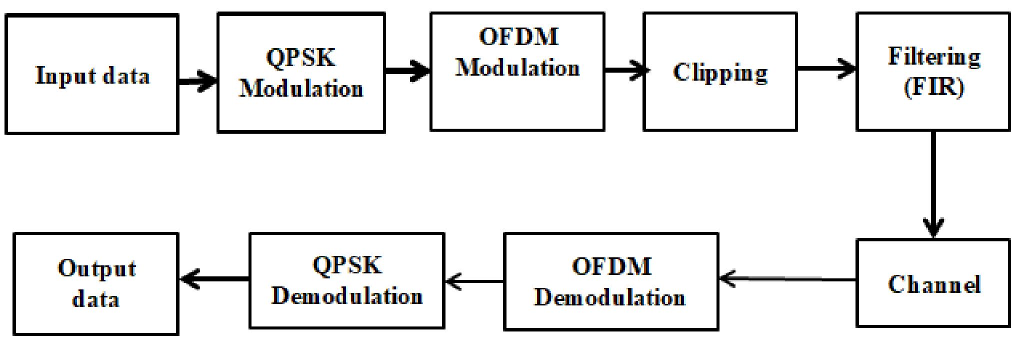

Fig. 11. OFDM with clipping and filtering [9]

5. MACHINE LEARNING (ML)

ML is a branch of artificial intelligence (AI) that enables computers to learn from and make decisions based on data without being explicitly programmed. ML algorithms identify patterns and relationships within data and use these insights to predict or classify new data points. Machine learning can significantly enhance PAPR reduction strategies by making them more adaptive, efficient, and effective, especially in complex and dynamic communication environments [40-42].
There are three main types of machine learning:
Supervised Learning: The algorithm is trained on labeled data, where the input-output pairs are known. The model learns to map inputs to the correct outputs, and once trained, it can predict outputs for new, unseen inputs. Examples: Classification (e.g., spam detection), regression (e.g., predicting house prices).
Unsupervised Learning: The algorithm is given unlabeled data and must find hidden patterns or structures within the data [40]. Examples: Clustering (e.g., customer segmentation), association (e.g., market basket analysis).
Reinforcement Learning: The model learns through trial and error, receiving rewards or penalties based on its actions, and aims to maximize cumulative rewards. Examples: Robotics, game AI.

5.1 Role of ML in PAPR Reduction

ML has emerged as a powerful tool in addressing complex problems across various fields, including telecommunications. Specifically, in the context of PAPR in OFDM systems, ML offers innovative solutions that can enhance the efficiency and performance of traditional methods. ML offers a promising approach to PAPR reduction in OFDM systems by enabling more adaptive, efficient, and effective strategies. By leveraging ML, communication systems can dynamically optimize their PAPR reduction techniques based on real-time conditions, historical data, and predictive modeling. While there are challenges in terms of complexity, data requirements, and integration, the potential benefits make ML an exciting area of research and application for improving PAPR reduction methods. As ML technology continues to advance, its role in PAPR reduction is likely to expand, leading to even more sophisticated and robust communication systems. Here's a detailed exploration of how ML can be leveraged for PAPR reduction:

5.1.1 Adaptive PAPR Reduction Strategies

1. **Problem Statement**: Traditional PAPR reduction techniques, such as Clipping and Filtering, SLM, and PTS, often involve a trade-off between complexity, distortion, and effectiveness. These methods are typically static, meaning they do not adapt to changing signal or channel conditions, potentially leading to suboptimal performance.
2. **ML Solution**: ML can be used to create adaptive PAPR reduction techniques that dynamically adjust based on real-time conditions. By training models on various channel conditions, signal characteristics, and system requirements, ML algorithms can predict the most effective PAPR reduction strategy for a given scenario.
    - *Reinforcement Learning (RL):* RL can be employed to continuously learn the optimal PAPR reduction strategy by interacting with the environment. The system receives feedback in the form of rewards (e.g., reduced PAPR without significant signal distortion) and adjusts its strategy accordingly.
    - *Supervised Learning:* Historical data can be used to train models that predict the best settings for PAPR reduction methods based on input features like SNR, modulation scheme, and channel conditions.
3. **Advantages:**
    - *Real-Time Adaptation:* ML models can adapt to changing environments, providing optimal PAPR reduction without manual intervention.
    - *Efficiency:* Reduces computational overhead by avoiding unnecessary computations for suboptimal techniques.
    - *Enhanced Performance:* Optimizes the balance between PAPR reduction, signal quality, and system complexity.

5.1.2 Predictive Modeling for PAPR Reduction

1. **Problem Statement:** Selecting the right parameters or techniques for PAPR reduction often requires a deep understanding of the system's behavior under different conditions. Traditional approaches may involve exhaustive testing and manual tuning, which is time-consuming and may not always yield the best results.
2. **ML Solution:** Predictive models, such as regression or classification models, can be trained to estimate the impact of various PAPR reduction techniques on system performance. These models can predict outcomes like BER degradation, power consumption, and signal distortion for different strategies.
   Support Vector Machines (SVMs): Can classify which PAPR reduction technique will likely result in the lowest PAPR for given input conditions [41-42].
   Neural Networks: Can predict the exact PAPR reduction and the resulting system performance metrics based on input parameters.
3. **Advantages:**
    - **Informed Decision-Making:** Allows for the selection of the most appropriate technique or parameter settings based on predicted outcomes.
    - **Optimization:** Ensures that the chosen method provides an optimal trade-off between PAPR reduction and other performance metrics.

5.1.3 Data-Driven Optimization

1. **Problem Statement**: Many PAPR reduction techniques involve parameter settings that significantly influence their effectiveness. For instance, in SLM, the choice of phase sequences can drastically affect PAPR reduction. However, finding the optimal settings is often a complex and computationally expensive task.
2. **ML Solution**: Machine learning can optimize these parameters by learning from historical data or through real-time exploration. For example:

   Genetic Algorithms (GAs): GAs can be used to evolve optimal phase sequences for SLM by simulating natural selection processes, where better-performing sequences are more likely to be selected for the next generation.
   Bayesian Optimization: Can be employed to find the optimal parameters for PTS or Clipping and Filtering by balancing exploration and exploitation in the parameter space.
3. **Advantages:**
   - **Efficiency:** Reduces the need for exhaustive search or manual tuning by automating the optimization process.
   - **Performance:** Can lead to better PAPR reduction with minimal signal degradation.
   - **Adaptability:** Continuously improves as more data becomes available, leading to better performance over time.

5.1.4 Real-Time PAPR Reduction

1. **Problem Statement**: In dynamic communication environments, such as mobile networks, the conditions can change rapidly. Traditional PAPR reduction methods may not be able to keep up with these changes, leading to inefficiencies and performance degradation.
2. **ML Solution:** Real-time PAPR reduction can be achieved through online machine learning techniques. These techniques allow the system to learn and adapt in real-time, continuously improving its PAPR reduction strategy.

   Online Learning: Algorithms like online gradient descent can update their models as new data comes in, allowing for real-time adaptation.
   Reinforcement Learning (RL): As mentioned earlier, RL can continuously refine the PAPR reduction strategy based on real-time feedback from the environment.
3. **Advantages:**
   - **Real-Time Adaptation:** Ensures that the PAPR reduction technique remains effective even as conditions change rapidly.
   - **Continuous Improvement:** The system gets better over time as it learns from ongoing operations.
   - **Low Latency:** Can provide immediate responses to changes in the environment, ensuring consistent performance.

5.1.5 Integration with Existing PAPR Reduction Techniques

1. **Problem Statement:** Traditional PAPR reduction techniques, while effective, may not always be sufficient in isolation, especially in complex scenarios. Integrating ML with these techniques can potentially enhance their performance.
2. **ML Solution**: ML can be integrated with existing PAPR reduction techniques to create hybrid approaches. For example:

   Hybrid SLM-ML: ML can predict the best phase sequences or even generate new sequences that are more likely to reduce PAPR effectively.
   ML-Enhanced Clipping: Instead of a fixed clipping level, ML can dynamically adjust the clipping level based on real-time signal analysis.
3. **Advantages:**
   - **Improved Effectiveness:** Enhances the performance of traditional techniques by making them more adaptive and context-aware.
   - **Seamless Integration:** ML can work alongside existing methods without requiring complete system redesigns.
   - **Scalability:** The hybrid approach can be scaled to more complex systems with multiple interacting components.

5.2 Advantages of Using ML for PAPR Reduction

- **Adaptability:** ML models can adapt to different signal and channel conditions, leading to more effective PAPR reduction.
- **Optimization:** Machine learning can optimize the balance between PAPR reduction and other performance metrics like BER and power consumption.
- **Automation:** Reduces the need for manual tuning of parameters, as the system can learn optimal settings over time.
- **Real-Time Application:** Machine learning can enable real-time decision-making and adjustments, crucial for dynamic communication environments [43].

5.3 Challenges and Considerations

While ML offers significant potential for PAPR reduction, several challenges need to be addressed:

- **Computational Complexity:** ML models, especially deep learning models, can be computationally intensive, which might not be suitable for all real-time applications.
- **Data Requirements:** Training effective ML models requires large datasets that represent a wide range of operating conditions. Collecting and processing this data can be challenging.
- **Model Interpretability:** ML models, particularly complex ones like neural networks, can be difficult to interpret, making it challenging to understand how decisions are made.
- **Implementation Overhead:** Integrating ML into existing systems can require significant changes to the system architecture, which may not always be feasible.

5.4 Various ML approaches for PAPR minimization

PAPR minimization is a critical issue in wireless communication, particularly in OFDM systems. High PAPR can cause inefficiencies in power amplifiers and degrade the overall system performance. ML offers innovative approaches to address PAPR minimization by leveraging data-driven techniques. Each of these ML approaches offers unique advantages for PAPR minimization, with the choice of method depending on the specific requirements of the communication system, such as computational complexity, real-time processing needs, and the nature of the OFDM signals. Combining these approaches often yields the best results, leveraging the strengths of different techniques. Here’s a breakdown of various ML approaches used for PAPR minimization:

TABLE III. VARIOUS ML APPROACHES FOR PAPR MINIMIZATION

Method	Description	Examples
2. Supervised Learning Approaches (Regression-Based Models)	Regression models predict the PAPR values based on input features extracted from the OFDM signal.	Linear regression, Support Vector Regression (SVR), and Neural Networks (NNs) can be trained to estimate the PAPR and apply corrective measures to reduce it.
Supervised Learning Approaches (Classification-Based Models)	These models classify signals into different PAPR levels and select the appropriate PAPR reduction technique based on the classification.	Decision Trees, Random Forest, and Convolutional Neural Networks (CNNs) classify the PAPR and adaptively apply clipping, coding, or selective mapping techniques.
3. Unsupervised Learning Approaches (Clustering)	Clustering algorithms group similar OFDM signals together based on their PAPR characteristics. This helps in applying specific PAPR reduction techniques to each cluster.	K-means clustering is used to identify clusters of signals with similar PAPR, followed by the application of appropriate reduction techniques.
Unsupervised Learning Approaches (Autoencoders)	Autoencoders can learn a compressed representation of the OFDM signal, which inherently has a lower PAPR. The decoder reconstructs the signal with a minimized PAPR.	Deep Autoencoders learn the low-dimensional features of the signal, reducing PAPR during the reconstruction phase.

4. Reinforcement Learning (RL) Approaches	RL-based models learn optimal PAPR reduction policies through trial and error. The agent interacts with the environment (OFDM system) and receives rewards based on the achieved PAPR levels.	Deep Q-Networks (DQN) and Policy Gradient methods can be used to dynamically adjust parameters like signal clipping levels or phase rotation to minimize PAPR.
5. Hybrid Approaches	These approaches combine multiple ML techniques to achieve better PAPR minimization. For example, a supervised learning model might first classify the signal, and then an RL agent might fine-tune the PAPR reduction technique.	A combination of CNNs for feature extraction and RL for decision-making in real-time PAPR reduction strategies
Deep Learning Approaches (CNNs)	6. CNNs can be used to capture spatial correlations in the OFDM signal and predict the PAPR, followed by applying reduction techniques.	A CNN model trained on OFDM signal samples can identify and suppress high PAPR components effective
1. Deep Learning Approaches (Recurrent Neural Networks)	RNNs, particularly Long Short-Term Memory (LSTM) networks, can model temporal dependencies in the signal sequence to predict and minimize PAPR.	LSTMs can be used to forecast future PAPR levels based on previous signal patterns, allowing proactive reduction.
7. Generative Adversarial Networks (GANs)	GANs can generate synthetic OFDM signals with low PAPR. The generator network produces signals, and the discriminator network ensures that the generated signals have desirable PAPR characteristics.	A GAN model can be trained to create OFDM signals that naturally exhibit lower PAPR, reducing the need for post-processing.
8. Transfer Learning	Transfer learning involves using pre-trained models on a related task and fine-tuning them for PAPR minimization.	A model pre-trained on a large dataset of communication signals can be adapted to minimize PAPR in a specific scenario with limited data.

6. CONCLUSIONS

This article has presented a thorough examination of the methods used in existing literature to decrease the PAPR in OFDM systems. We explored a range of conventional methods, innovative strategies, and upcoming developments in the sector. The literature study found that traditional methods, including as PTS, SLM, and clipping, together with additional approaches, have been extensively researched and used for reducing PAPR in OFDM. These technologies have shown substantial gains in decreasing the PAPR. Nevertheless, they often exhibit some disadvantages, like heightened intricacy, BER, and distortion. An important development in recent years has been the use of machine learning algorithms for reducing PAPR. ML methods have shown significant promise in tackling the issues related to the PAPR in OFDM systems. These strategies use data-driven learning and optimization to intelligently and adaptively decrease the PAPR while maintaining system performance.

Conflict of Interest

The authors declare that there is no conflict of interest.

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