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Machine Learning Techniques for Efficient PAPR Reduction: A Theoretical Perspective

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Abstract –**The requirement for high data rates in current wireless communication systems has led to the large deployment of OFDM technique in 4G LTE networks and is anticipated to continue in future 5G and 6G networks. Although there are many benefits of the OFDM, the Peak-to-Average Power Ratio (PAPR) problem is a severe drawback to OFDM. High PAPR causes inefficiency of power amplifiers, signal distortion, spectral regrowth that degrades the performance of system. The most popular ones are through Clipping and Filtering, Partial Transmit Sequence (PTS), and more recently, Selected Mapping (SLM). But they frequently encounter trade-offs in signal quality, computational complexity, and performance efficiency. Due to these constraints, adaptive and efficient methods are in demand for PAPR mitigation in OFDM systems, and machine learning (ML) has emerged as a promising approach. In this work, a theoretical overview of Machine Learning-based methods applied to PAPR mitigation is provided, and several neural network models including Artificial Neural Networks (ANN), Deep Neural Network (DNN), and Reinforcement Learning (RL) are discussed based on their benefits and limitations. The paper also discusses future avenues for research on hybrid models, federated learning, and real-time optimization techniques for 5G and beyond. ML can be utilized to further augment PAPR reduction, leading to advanced versatile and adaptive communication systems in emerging wireless technologies.**

Keywords – **ANN, DNN, Machine Learning, OFDM, PAPR, PTS, Reinforcement Learning, SLM, etc.**

I. INTRODUCTION

Wireless communications technology has advanced dramatically over the last several decades to support rising demands for higher data rates, enhanced reliability, and better user experience. OFDM has gained prominence as the most widely used modulation scheme of modern and future wireless systems. The importance of OFDM in modern communication has been made evident through its adoption by standards including 4G LTE as well as its anticipated use in 5G and beyond [1]. Nevertheless, OFDM indeed comes with many advantages, but also its own challenges. Peak-to-Average Power Ratio (PAPR) is one of the major problems of OFDM systems that have been extensively studied through both academia and industry 2.

PAPR is an important observable in evaluating performance, which is defined as the ratio of the peak power of a transmitted signal to the average power. In OFDM systems with high PAPR, the power amplifiers (PAs) utilized for signal transmission can face significant inefficiencies. The main drawback of non-overlapping PAs is that they are commonly required to achieve a larger dynamic range, which leads to larger power consumption and higher complexity [4]. Moreover, high PAPR can result in signal distortion, poor linearity and cross talk between adjacent frequency bands, all of which adversely affect the overall performance of the communication system [5]. Specifically, in terms of the inevitable growth of demand for high-capacity, high-throughput communication for 5G and 6G networks, reducing PAPR turns into a progressively pressing quest for different researchers and engineers [6] [7]. Not only does PAPR minimization guarantee/ensure efficient power utilization, but it also allows the utilization of more power-efficient, economical components.

There are several techniques that have been recommended over the years to solve the high PAPR problem in OFDM system. Besides classical approaches, e.g., Clipping and Filtering, Partial Transmit Sequence (PTS), and Selected Mapping (SLM) which are all signal manipulation based and achieved different levels of success [8]. However, these methods are computationally simpler but sometimes exhibit trade-off between the PAPR reduction and other performance metrics e.g., signal distortion, computational complexity, and robustness of the system [9] [10]. Additionally, the evolution of communication channels and the escalation of system complexity make it clear that conventional techniques may not be adequate to handle the requirements of future wireless networks [11].

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In the face of such challenges, Machine Learning (ML) has emerged as a potential paradigm to address the PAPR problem in OFDM systems. Machine Learning (ML) is a highly promising concept to enhance PAPR alleviation techniques and optimize them even further Based on executed supervised and unsupervised learning concepts. In contrast to conventional approaches, ML-based solutions can learn from data, adapt to evolving environments, and constantly enhance their performance [12]. These approaches are still limited to static features, and hence, novelty can be found in dynamically optimized PAPR in real time communication systems that are inherently variable in multiple parameters like channel conditions, traffic load, and user mobility [13]. Moreover, ML algorithms are capable of exploring complex, high-dimensional spaces, which makes them particularly suited to the nonlinearities and complex interdependencies characterizing PAPR ratio reduction [14].

Recently, there has been an increasing interest in the application of ML for the design and optimization of OFDM systems [1]–[10]. Several ML-based approaches, such as Artificial Neural Networks (ANN), Deep Neural Networks (DNN), and Reinforcement Learning (RL) models, have been proposed to solve the PAPR reduction issue 15. Recently, other methods are also being developed through the use of machine learning models that train the system to find optimal signal processing strategies through large datasets, substantially improving the overall PAPR reduction performances [17]. Moreover, the integration of massive antenna arrays along with multi-input multi-output (MIMO) systems with these prediction models can lead to higher efficiency solutions. Nevertheless, ML for PAPR reduction is still in its infancy and numerous challenges persist. The main drawbacks are large-scale training data requirement, overfitting problem, and computational complexity for real-time implementation [18].

In this review paper, the theoretical basics of the machine learning techniques used for effective PAPR reduction in OFDM systems has been discussed. Through a systematic review of the existing state-of-the-art works on ML techniques, their pros and cons, and finally their application scenarios, this study will provide a useful reference for those researchers, engineers, and practitioners working toward fourth-generation wireless links [19]. It aims to provide you with a comprehensive understanding of the way ML can be used to enhance PAPR reduction strategies, point out existing gaps in the literature, and recommend directions for future research.

The remainder of the paper is structured as follows: in Section 2, the OFDM modulation is introduced along with its principles and the PAPR problem. In section 3, we discuss conventional methods for reducing PAPR, addressing their benefits and draws back. Section 4 reviews the state of the art for different machine learning techniques in PAPR reduction, specifically supervised learning algorithms including neural networks and reinforcement learning models. In Section 5 we cover the associated challenges for the application of ML to the PAPR reduction problem, such as data collection, the computational complexity of model implementation of optimization, and the deployment of online models. Also, future directions towards ML-aided PAPR mitigation, particularly in the context of more advanced paradigms of communication systems. Lastly, Section 6 wraps up the paper with a summary of key findings and recommendations for future work.

Motivation to build PAPR reduction techniques which had been ensured in favorable conditions for practical implementations considering 5G and beyond systems employing OFDM-based communication systems. Machine learning, known for its ability to adapt and high-performance optimization potential, offers an interesting new avenue to accomplish this. This review will help fill this knowledge gap by discussing the foundations and recent progress in the field of ML based PAPR reduction methods.

II. Background on OFDM Modulation and PAPR Problem

OFDM (Orthogonal Frequency Division Multiplexing) A multiplexer method of modulation that uses a massive amount of data. Its acceptance is so widespread that it is also supported in standards such as 4G LTE, and it is likely to continue to play an important role in 5G and future 6G networks. OFDM is a robust waveform for high-data-rate transmission in multipath fading and interference environments. But one of the essential disadvantageous OFDM signal has Peak-to-Average Power ratio (PAPR) which affects the efficiency of communication system. This section gives the essential concepts of OFDM modulation with detailed discussions on the PAPR problem.

A. Overview of OFDM Modulation

Orthogonal frequency division multiplexing (OFDM) is a multi-carrier modulation scheme in which a signal with a very high data rate is divided into several lower data-rate sub-signals, each of which are transmitted in parallel over a number of ortho-normal carriers. It allows communication

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systems, especially broadband communication systems, to maximize the utilization of the available bandwidth.

1. *Basic Working Principle of OFDM*

Orthogonal Frequency Division Multiplexing (OFDM) converts data into multiple parallel streams, where each stream is modulated on a subcarrier (by a process known as Inverse Fast Fourier Transform, IFFT). The frequency components of the subcarriers are orthogonal, so their mutual interference is avoided, which allows full use of the available bandwidth [20].

A high-level view of the OFDM transmission process consists of the following steps:

- Data Segmentation: The data stream is divided into separate sub-streams, with each of them assigned to a unique subcarrier.
- IFFT: The sub-streams are fed into the according IFFT to generate time-domain signals.
- Addition of Cyclic Prefix (CP): To mitigate the effects of multipath interference, a cyclic prefix (CP) is added to the transmitted signal. Broadly speaking, the CP assists with inter-symbol interference (ISI) reduction by providing an interval between OFDM symbols.
- Transmission: The time-domain OFDM (orthogonal frequency division multiplexing) signal is transmitted through the communication channel.

On the receiver side, the process works in the other way, where the Cyclic Prefix is eliminated and Fast Fourier Transform (FFT) is performed to get the data.

2. *Advantages of OFDM*

- Spectral Efficiency: With the orthogonality among the subcarriers, tightly packed subcarriers do not contribute to interference, leading to efficient utilization of available spectrum [21].
- Resistance to Multipath Fading: With its high level of resistance to multipath interference, OFDM is an excellent candidate for wireless communication, making it especially useful in mobile environments [22].
- Flexibility: OFDM can support multiple types of modulation schemes (e.g., QPSK, QAM), and it is flexible to different channel conditions (i.e., time-varying channels) [23].

These advantages has led to its being the modulation scheme of choice for new high-speed data transmission wireless systems.

B. The PAPR Problem in OFDM

Although OFDM has many advantages, it has an inherent limitation in the form of Peak-to-Average Power Ratio (PAPR). From the definition of PAPR, it is the ratio of the peak power of transmitted signal to the average power, which is an important metric for the evaluation of performance in communication systems.

1. *Definition and Calculation of PAPR*

The PAPR of an OFDM signal is mathematically defined as:

$$PAPR = \frac{\max|x(t)|^2}{E[|x(t)|^2]} \tag{1}$$

Where:

- $\max|x(t)|^2$ is the maximum instantaneous power of the signal.
- $E[|x(t)|^2]$ is the average power of the signal [24].

In other words, the PAPR is the ratio between the peak value and average power of the signal, and a high PAPR can lead to several performance degradation in a communication system.

2. *Causes of High PAPR in OFDM*

High PAPR in OFDM systems is mainly attributed to the constructive addition of the various subcarriers at the receiver. As OFDM is making use of multiple subcarriers some of these can be in phase in time or constructively, such results as signal peaks in the time domain.

- Constructive Individuation: In OFDM, a signal comprises various subcarriers. This causes the amplitudes to be summed up when the subcarriers are in phase, which can give peak power at certain timings [25].
- More Subcarrier Use: Usage of more subcarriers in an OFDM system will also increase the PAPR. Since the number of subcarriers is larger, simultaneous constructive interference is more probable leading to rising peak power [26].

The PAPR is not fixed and is time varying, thus hard to predict and manage. This variability must be managed to achieve optimized system performance.

3. *Implications of High PAPR*

Very high levels of PAPR pose various challenges in effective system operation in OFDM-based systems, particularly in terms of power amplifier efficiency and signal quality.

- Efficiency of Power Amplifier: Power amplifiers are generally designed for

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maximum power of transmitted signal. This leads to the inefficient utilization of the power as well as higher energy consumption because the amplifiers will need to operate over a broader dynamic range to compensate for the high PAPR [27].

- Signal Distortion– If the peak power goes beyond the amplifier's range of operation, a distortion occurs called clipping. Clipping adds nonlinearity to the signal and leads to distortion and signal quality degradation [28].
- Interference and Spectral Regrowth: Higher PAPR can lead to emissions outside the allocated bandwidth and therefore cause interference to the adjacent frequency bands. This regrowth introduces spectral failure leading to degradation in the spectrally efficiency and interruption through other communication systems [29].
- High Computational Load: High PAPR signals need an enhanced signal processing techniques for produce mitigation increases the computational load on the system, especially in real-time applications [30].

Hence managing the PAPR is among the notable parameters for the integrity and also the effective operation of the paradigms of OFDM-based interaction systems.

C. Traditional Methods for PAPR Reduction

There have been some classical approaches for PAPR reduction in OFDM systems. The techniques generally include signal distortion, signal scrambling, and coding schemes.

1. Clipping and Filtering

The simplest method to reduce PAPR is clipping. It is responsible for clipping the amplitude of the signal and prevents overdrive. This approach may still distort the signal and raise the signal bit error rate (BER).

- Clipping: When the signal crosses a limit, it is clipped. This lowers the peak power but can lead to severe distortion [31].
- Filtering: This is done post-clipping to get rid of out-of-band distortion and to recover some of the lost signal quality.

This approach has the computational advantage, but at the cost of distortion and a possible performance drop.

2. Partial Transmit Sequence (PTS)

PTS works by first dividing the OFDM signal into multiple blocks and then applying some phase shifts to those blocks in order to reduce PAPR. Despite the significant reduction of PAPR using PTS method, it has a high computational complexity and so it is not suitable for real-time applications [32].

3. Selected Mapping (SLM)

For SLM, it creates a series of OFDM signals with different phase sequences based on the input information bits and selects one with the minimum PAPR for transmission. Although SLM is efficient in PAPR reduction, it involves transmitting side information which impairs its spectral efficiency [33].

D. The Need for Machine Learning in PAPR Reduction

Traditional techniques work effectively but usually compromise the balance between PAPR reduction, computational complexity, and system performance. While this is still true today, new technologies for wireless communications are emerging, such as 5G and future 6G networks, which create an immediate necessity for systems which can substantially increase performance in regard to both the signalling and channel propagation in an adaptive way to manage PAPR in OFDM systems.

This problem can be addressed using Machine Learning (ML) which holds the promise of dynamically optimizing the PAPR reduction. ML technologies are able to learn from data, adapt to changing environments, and improve their performance over time. Conventional optimization methods work with a set of pre-defined rules and defined configurations, while ML enables to search dynamic solution space and generate adaptive solutions in real-time [34].

III. Traditional Methods for PAPR Reduction

PAPR mitigation is still a significant problem for OFDM networks, especially in large-capacity wireless technologies such as 5G and above. In classical PAPR reduction approaches, several techniques have been proposed over the years. Such techniques can be classified into signal distortion, signal scrambling and coding. Here we analyze these traditional approaches in-depth, showing their principles, benefits, and weaknesses.

A. Signal Distortion Techniques

One of the most straightforward and widely used approaches to mitigate PAPR is to apply signal distortion techniques. These techniques directly distort the transmitted signal, either by clipping the signal or by using more advanced techniques such as Active Constellation Extension (ACE). Although these techniques are relatively simple to implement, they tend to introduce performance degradation, like

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stronger signal distortion or a higher BER (bit error rate).

1. Clipping and Filtering

The simplest method for reducing PAPR is clipping. This technique consists of establishing a threshold value and clipping the signal every time its amplitude surpasses this threshold value. Clipping reduces the peak power which translates into a reduced PAPR, but brings nonlinear distortions to the signal.

- Clipping: This method simply clips the signal when its amplitude exceeds a certain threshold, which effectively drops the peak power. Yet, such process leads to generated signal distortion, resulting in high BER, e.g. when clipping level is too low [35].
- Filtering: It is common to apply a filter to correct for the distortion introduced by clipping. Filtering attenuates out-of-band spectral components, aiding in the restoration of some signal quality. Nonetheless, this filtering may not work too effectively if clipping is high, resulting in the large loss of signal power [36].

Although clipping and filtering are not computational heavy, they which degrade signal quality and is not suitable for cases which are required to maintain low BER. However, they are still a good choice for certain low-end applications.

2. Active Constellation Extension (ACE)

Another PAPR reduction method is based on distortion which is known as ACE. "This technique expands the constellation points of the signal outwards, creating equivalently new 'feasible regions' that cause the signal amplitudes to be more evenly distributed." ACE is used to reduce PAPR by lowering peak values by modifying the constellation.

- Advantages: The ACE outperforms the PAPR reduction strike while maintaining the severe distortion at a moderate level and that makes it more preferable in high-class communication systems.
- Drawbacks: The primary disadvantage of ACE is that its constellation points must be optimally tuned carefully, thus increasing the computational burden on the system and incurring significant delivery power afterwards to send (effectively) the expanded constellation points in competition [37].

ACE can leverage flexibility not achievable by clipping, and it can be optimized for a lower trade-off between PAPR and BER.

B. Signal Scrambling Techniques

Signal scrambling techniques operate in an indirect way on the transmitted signal with the aim of spreading the power of the signal in time so as to lower the probability of high peaks. While these methods do not incur the severe distortion from clipping and filtering, they may involve additional processing or side information at the receiver.

1. Partial Transmit Sequence (PTS)

PTS is another extensively researched method for reducing PAPR in OFDM systems. PTS is a well-known technique to mitigate the PAPR if the PAPR-aware OFDM signal is divided into a number of sub-blocks, and phase rotation is then applied to each of the sub-blocks in order to construct the signal whose PAPR is minimized. In this phase rotation, we also search for the set of phase factors that minimize the PAPR.

- Processing: The input data stream is divided into a number of sub-blocks which are phase-optimized through a search process. Then, these sub-blocks are recombined to reconstruct the desired signal, with PAPR that is significantly lower than the PAPR in the initial signal.
- Benefits: With little signal distortion, PTS can achieve significant PAPR reduction and can be regarded as one of the most efficient conventional techniques.
- Cons: The biggest downside of PTS is its computational complexity. The procedure is computationally demanding, particularly when more sub-blocks or increased modulation order is considered [38], since it involves trial-optimization of phase factors multiple times. Furthermore, since PTS needs to pass side information, it causes spectral efficiency loss.

For systems where computational resources are available, PTS is one of the most promising approaches to reducing PAPR, despite its complexity.

2. Selected Mapping (SLM)

Another signal scrambling scheme is SLM [49] where multiple variants of the OFDM signal are generated based on different phase sequences. The signal with the minimum fall in PAPR is then selected to make the transmission. The receiver needs to know which phase sequence was used, thus some side information has to be sent along with the signal.

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- Process: The OFDM signal is processed with a specific set of phase shifts, resulting in multiple candidate signals. The candidate with the least PAPR is picked for sending.
- Benefits: Compared with clipping, SLM is less sensitive for the signal distortion and achieves a considerable decrease in PAPR.
- Drawback: The need to send side information decreases the overall spectral efficiency. The more candidate signals, the higher the computational complexity [39].

Although SLM can significantly reduce PAPR, it introduces the trade-off between PAPR reduction and system efficiency.

C. Coding Techniques for PAPR Reduction

Coding techniques are widely used to change the signal structure or penetration at special coding strategies to mitigate PAPR. These techniques are more developed than signal distortion and scrambling techniques and usually require some type of redundancy or error correction to work as well.

1. Tone Reservation (TR)

It is a method in which a section of the subcarriers is reserved to transmit further tones for peak-signaling to minimize the peaks of the transmitted signal. These reserved tones are used for reducing high PAPR since they cancel peak powers.

- Process: : Cancellation tones insertion requires reserving access to a certain set of subcarriers, this is performed in order to minimize the PAPR. So the reserved sounds are precisely dispensed into the signal, following the high power peaks.
- Benefits: The TR can reduce the PAPR effectively with a minimum of signal distortion. Additionally, it can provide spectral efficiency depending on how many tones are reserved according to system needs.
- Drawbacks: The major drawback of TR is the loss in spectral efficiency because of assigning the subcarriers for cancellation tones. Also, the approach supposes knowledge about the channel, which is not always easily available [40].

While TR can drastically improve PAPR performance, the overall performance in terms of system throughput and system complexity needs to be verified.

2. Tone Injection (TI)

TI is a technique in which certain tone values are injected at intervals into the signal that are intended to cause high power peaks to occur much less often. PAPR is reduced by using these tones, as they do not contain any information.

- Process: TI accomplishes this by injecting extra tones at certain frequencies to distribute power throughout the signal and, in turn, reduce high peak values.
- Benefits: TI is of low-complexity design and requires no side information transmission.
- Cons: Like TR, TI impacts spectral efficiency since it reserves a section of the signal for tones that don't convey data. Furthermore, TI needs to know more channel information to improve the positioning of the tones [41].

TI gives the simpler bitwise alternative to such schemes like TR but comes at the expense of reducing spectral efficiency.

D. Summary of Traditional PAPR Reduction Methods

Conventional PAPR reduction techniques like clipping, PTS, SLM, TR and TI, have shown a different level of success in solving the PAPR problem in OFDM systems. Different types have their own merits and demerits, as to computational complexity, signal distortion, spectral efficiency, and system performance. Although these methods are essentially beneficial in a large number of situation, they may not always be-fit to the strict specifications of current wireless communication systems, especially in within the idea of 5G and beyond. Consequently, there is an increasing demand to find these more dynamic and smarter solutions that the Machine Learning can provide.

IV. Machine Learning-Based Techniques to Reduce PAPR

The problem of Peak-to-Average Power Ratio (PAPR) in Orthogonal Frequency Division Multiplexing (OFDM) systems can be effectively solved using machine learning (ML) techniques. Tasks related to PAPR reduction can be complex with largescale data and employment of ML based techniques to solve the issues has become very attractive given their adaptive nature in environments. Such techniques provide substantial benefits related to flexibility, real-time optimization, and computational efficiency. The rest of this section will give a detailed view of ML methods for PAPR reduction, including supervised learning, unsupervised learning, and reinforcement learning (RL) methods with their challenges and future trends.

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A. PAPR Reduction Techniques based on Machine Learning

The ML based methodologies provide a data-driven framework for refining the PAPR reduction algorithms in OFDM systems. Whereas conventional methods are based on static rules that do not change over time, ML algorithms can learn from data and change according to variations in channel conditions and communication environments. ML can help in PAPR reduction by learning patterns from historical data and applying it to the signal processing and power allocation process.

For PAPR reduction, ML methods can be classified in three main categories: supervised learning, unsupervised learning, and reinforcement learning. Each of these methods has its advantages depending on the characteristics of the communication system.

- Supervised Learning is the type where a model is trained on the labeled dataset, i.e. there is a definitive relation between the input features and the output. It is trained for a relationship between input (Signal parameters) and output (PAPR).
- Unsupervised methods learn patterns and structures in data without relying on labeled data. They can be used to group signals with similar signal characteristics and to determine the best configuration for minimizing peak average power (PAPR).
- Reinforcement Learning is a type of machine learning that deals with how agents ought to take actions in an environment in order to maximize some notion of cumulative reward, thus minimizing the PAPR.

So, all of the techniques have some specific advantages in the context of the PAPR reduction problem and are application dependent as well as dependent on the nature of the communication system.

B. Supervised Learning for PAPR Reduction

One widely used ML technique for PAPR reduction is the supervised learning approach. It is based on the training of a model using input-output pairs from a dataset, meaning that this model learns how to associate the input signal (or subcarriers) to the output signal with reduced PAPR in this case. As input information enters the media, the models taught through supervised learning are capable of anticipating PAPR reduction techniques.

1. Artificial Neural Networks (ANN)

Artificial Neural Networks (ANNs) is a powerful model that is capable of capturing complex functions mapping inputs to outputs. This property is especially useful when the relation between the individual input and output is a nonlinear one, as it is normally the case for PAPR reduction methods.

ANN model can be trained to learn the parameters for the process of reducing the peak to average power ratio (PAPR) in orthogonal frequency division multiplexing (OFDM). In particular, ANNs can be trained on a diverse dataset of OFDM signals with varying PAPR values, and the resulting model can learn to predict configurations of the signal that would yield low PAPR given a set of input features.

- Pros: ANNs work for problems in which defining an input-output relationship is not obvious. Their capacity to approximate complex nonlinear functions makes them highly suitable for PAPR reduction techniques for OFDM systems [42]. In addition to that, ANNs can also optimize different system parameters like power allocation, which will enhance the entire system performance.
- Cons: One of the significant challenges of using ANNs is the possibility of overfitting the model to the training data; this is especially true if the dataset used for model training is small or contains limited conditions for the diverse communication environments. Furthermore, ANNs need large volumes of labeled data to produce valid feature representations, which can also make training computationally expensive (especially for deep networks) [43].

2. DNN (Deep Neural Networks)

A DNN can be considered an ANN structured with more than one hidden layer, allowing it to learn complex hierarchical structures of input data. Utilizing deep learning networks, or DNNs, becomes viable due to these networks' depth, which dramatically increases the potential numbers of patterns they can learn in the data, thus significantly enhancing achievable performance (especially in PAPR reduction).

DNNs have also been used to reduce PAPR by mapping a given OFDM signal to an optimized output. Such networks can leverage the non-linear relationships between signal parameters and its peak-to-average power ratio (PAPR) to mitigate it more effectively.

- Pros: DNNs can process high-dimensional input data and are capable of mapping complex dependencies, so they can be applied to an OFDM signal with a huge number of subcarriers. It has been shown that deep structures trained in a supervised

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manner outperform shallow networks [44] in applications dealing with complex structures of signals at high dimensions.

- Cons: To generalize well and not overfit, DNNs need millions of data points. Moreover, the training of deep neural networks is computationally challenging, taking a considerable amount of processing power and time. Also, DNNs have an often low interpretability with methods that makes it difficult to understand why they make certain decisions.

3. Support Vector Machine (SVM)

Support Vector Machines (SVM) are supervised learning models used for classification as well as regression tasks. For the purpose of reducing PAPR, SVM can be used to determine the optimal parameters for signal arrangement to achieve the lowest PAPR values.

Application Example: SVM for PAPR Reduction: SVM can be used to classify the optimal phase shifts or signal parameters in order to minimize PAPR in an OFDM system. SVMs are trained on labeled data, which allows them to classify the signal configurations according to their PAPR values, and subsequently, they can choose the best configuration for transmission [45].

- Pros: SVMs are a powerful tool that makes use of a kernel trick to map non-linear input space features onto a high-dimensional feature space, creating a hyperplane which separates the two classes. They are particularly useful when you have a small dataset with complex, high-dimensional features.
- Cons: Generally slow to train, especially with large datasets. Howbeit, on top of this, the use of hyper-parameters like the kernel parameter and regularization parameters makes SVM very difficult to use for PAPR reduction.

C. Unsupervised Learning for PAPR Mitigation

Cluster analysis is a technique of unsupervised learning that is used to identify groups or clusters in the data without labeled samples. Such approaches are particularly useful when the objective is either to analyze the intrinsic structure of the data or to discover groupings of signal configurations inducing low PAPR.

1. K-Means Clustering

K-Means clustering is a type of unsupervised learning in which a data set is divided into k clusters, which are defined as sets of items closer to each other compared to the others. K-Means may be used for PAPR reduction by clustering the various signal configurations on the basis of the PAPR, hence determining the configuration of lowest PAPR level. The algorithm will group the OFDM signal with similar parameters. Then, the signal with minimum PAPR in each cluster is selected for transmission.

- Pros: The simplicity and efficiency of K-Means make it easy to implement and effective for real-time applications. It is also simple to implement and does not require annotated data.
- Limitations: As K-Means is reliant on the initial cluster centroids, it can converge on sub-optimal results. It is also restricted in the complexity of relationships it can model.

D. Reinforcement Learning (RL) for PAPR Reduction

It is a sub-field of machine learning that trains an agent through a series of interactions with an environment. Based on its actions, the agent receives rewards or penalties and learns how do to so the best and reach its long-term goals. RL techniques can dynamically modify signal parameters in a way that leads to lower PAPR without compromising system performance.

1. Q-Learning

Q-Learning is a model-free RL algorithm that is commonly applied to such optimization problems like PAPR reduction. In Q-learning, an agent learns to choose actions, for example, adjusting the signal parameters that is based on the current state, for example PAPR levels and channel conditions.

- PAPR Reduction in Q-learning: The agent acts by selecting actions to update the transmission parameters (phase shifts or power levels) with the goal of minimizing PAPR. In this way, the agent is rewarded proportional to the reduction in PAPR and is able to learn the optimal actions over time.
- Pros: Q-learning can perform online optimization, and will adjust to differing and changing network conditions. It is also very flexible and can be used to address a wide range of PAPR reduction issues [46].
- Limitations: The primary difficulty with Q-learning is that the process becomes too computationally expensive, especially when there are a large number of possible actions. Another downside is that it needs a lot of training examples to learn good strategies.

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2. Deep Q-Networks (DQN)

DQNs generalize Q-learning with the addition of deep neural network to approximate the Q-values. DQNs help us solve even more complex problems now such as PAPR reduction in OFDM systems, for which both the state and action spaces tend to be large.

- Use in PAPR Reduction: By approximating the Q-values with a neural network, DQNs can learn to optimize PAPR reduction strategies over time, enabling more effective decision-making in complex systems.
- Pros: DQNs are capable of handling high-dimensional data and large action space and thus are very powerful for complex PAPR reduction tasks [47].
- Limitations: DQNs tend to require large quantity of data to be trained effectively and are computationally heavy, which is more complex in real-time applications.

Although machine learning methods provide tremendous enhancements for PAPR reduction, some challenges must be solved. A key challenge is the need for larger and more diverse training datasets to avoid overfitting. Moreover, because DNNs and DQNs are deep models, training them can be computationally expensive, making it difficult for real-time systems. The interpretability of ML models is another worry, especially in the case of communication systems, where something that is transparent and explainable is considered a necessity.

In future works, hybrid models from hybrid ML techniques should be created to leverage the best of each of them– the combination of reinforcement learning and deep learning may yield enough flexibility to achieve a more efficient PAPR reduction. Additionally, leveraging ML-based approaches alongside next-generation communication technologies like massive MIMO and 6G systems shows potential to enhance PAPR reduction in these evolving wireless frameworks.

V. Challenges and Future Directions

Although machine learning (ML) techniques have exhibited significant promise in reducing the Peak-to-Average Power Ratio (PAPR) of Orthogonal Frequency Division Multiplexing (OFDM) systems, there are multiple challenges associated with these techniques. Therefore, we need to focus on resolving these challenges to feasible ML-based approaches in practical large-scale communication systems looking into the future. In this part, we highlight important challenges and outline future directions for the ML-based approaches in PAPR reduction techniques.

A. Key Challenges in Machine Learning based PAPR Reduction

Machine learning algorithms lead to a considerable gain in PAPR mitigation, however, there are still several hurdles to be cleared before the intents can be executed in the real-world systems. These challenges can generally be divided into data challenges, computational challenges, and model challenges.

1. Data-Related Challenges

Apart from the algorithms devised with ML, training data is the backbone of ML-based PAPR reduction. The key data challenges are as follows:

(Machine learning, especially deep learning, needs big datasets of data points to train its models.) The gathering of sufficient, quality data for PAPR reduction can be extremely difficult, especially for real-time/dynamic communication environments. In order for the model to generalize well and yield effective PAPR reduction, it must be trained on samples from a wide variety of channel conditions, modulation schemes used, and types of interferences present.

- Rich Training Data: The training data for ML models has to be diverse encompassing a variety of scenarios from variations in channel conditions, user mobility, and network configurations. Overfitting occurs when the model fits too closely to the training data, which is particularly concerning when there is little diversity in the data.
- Data Labeling: While supervised learning approaches such as neural networks and support vector machine (SVM) require the data to be labeleded. The problem over here is, this takes a lot of time and it cost a high amount of money to do manual labeling in complex communication systems.
- Real-time Data Generation: Since PAPR reduction should be done in real-time in practical communication systems (particularly in 5G and beyond), such an implementation necessitates the ongoing collection and processing of data, which hinders the adoption of ML methods for PAPR reduction.

2. Challenges in Computation

Training machine learning models, and in particular deep learning models, requires a lot of computational power and comes with a series of challenges:

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- Dataset Size: DNNs and other complex ML techniques, in particular, may need significant training hours, especially when the size of the dataset is huge and its dimensions are high. As a result, these approaches are challenging to implement in low-latency systems where real-time data processing is required due to the high processing power they require.
- It has been noted that while RL approaches, such as Q-learning and deep Q-networks (DQNs), can optimize continuously in real time, the computational complexity of performing continual training under dynamic environmental conditions can be costly. This needs to be implemented in a timely manner, without compromising the efficiency necessary to enter the evolution of the channel or the variations in PAPR.
- Hardware Requirements: The computational cost of training and inference can be prohibitive, this is especially true for practical implementations. This may require efficient hardware accelerators like Graphics Processing Units (GPUs) and Tensor Processing Units (TPUs), making deployment harder and more expensive.

3. Model Related Challenges

The proposed model and its design are the key ingredients for effective implementation of ML-based PAPR reduction. At least a couple of model-related challenges have to be solved:

- Overfitting and Generalization: Overfitting is the effect when your ML model is having a good accuracy on the training data but it is not able to generalize on the data which was never seen before. Such behavior is particularly troublesome for communication systems where the channel conditions and signal characteristics can vary. A strong model that generalizes well to new, unseen conditions is vital for the real-world performance [48].
- Interpretability of Models: Deep learning models, despite being powerful in nature, are usually black boxes. These models are not interpretable, and it is hard to explain why a process concludes in a certain way. Model interpretability is vital in communication systems, where system-wide parameters, such as power allocation or signal shaping, are impacted by user decisions.
- Between Complexity and Model Size: Model Size matters a lot for the model performance and its deployment. Although bigger models can learn more complex relationships and often deliver lower error rates, bigger models also pay with higher computation costs, memory consumption, and slower inference. Balancing between complexity of models and efficiency is a challenge that keeps on persisting.

B. Future Directions in ML-Based PAPR Reduction

However, the prospects for ML-based PAPR reduction are bright. Using emerging technologies and exploring trending research topics create a wide range of opportunities for using ML methods for effective real-time and energy-efficient PAPR mitigation in OFDM systems. Here are some of the future trends discussed:

1. Hybrid Approaches and Transfer Learning

Hybrid models that incorporate multiple routes have gained attention at this point to tackle overfitting issues and data limitations encountered in the methods described here. Such mixed models can lead to better adaptability and efficiency. Therefore, in this strategy, whilst supervised learning will help to train the first model, reinforcement learning will iterate and make the model better by simulating it to interaction with real-time data.

One example of this technique is transfer learning, which allows the learning from one domain to be transferred over to another domain. For PAPR mitigation, transfer learning enables the adaptation of trained models from simulated data to real environments, which is too costly and time-consumptive, considering the limited amount of available datasets [49]

2. Sleep Quality Awakens after Federated Learning on Distributed Networks

Given the emerging trend of distributed networks such as 5G and beyond, federated learning provides a new paradigm to collaboratively train ML models on many devices without needing to centralize data. The key idea of federated learning is to perform local model training on each device and send only model updates to a central server, which reduces data communication cost and improves data privacy.

PAPR reduction has specific challenges in large-scale systems requiring real-time optimization based on heterogeneous devices, channel conditions, and network topologies, whereby federated learning will be particularly beneficial in handling the challenges due to its compatibility with privacy-aware designs.

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Federated learning [50] improves the adaptability and scalability of ML-based PAPR reduction systems while protecting data privacy by allowing models to be trained in a distributed nature.

3. Real Time and Low Latency Solutions

However, demanding fast inference times due to the increasing need for real-time communications and low-latency systems, require these ML based PAPR reduction methods to be optimized. Techniques like model pruning, quantization, and knowledge distillation may be employed to decrease the complexity and computational expense of deep models, allowing them to be used in real-time systems.

This includes developing edge-computing solutions that can help to offload processing to edge devices rather than relying entirely on central servers, allowing for more rapid decision-making. With the blend of ML models and edge computing, the system can update itself rapidly based on network condition changes, while executing PAPR reduction techniques in a real-time manner with minimal latency.

4. Merged with 5G and 6G Networks

PAPR reduction can take helpful advantages of deploying 5G and future 6G networks. As a result of the exponential increase in connected devices and the need for ultra-reliable low-latency communication (URLLC), the demand for efficient PAPR reduction techniques will increase. Through this evolution, ML-based methods will be pivotal, as they will allow networks to dynamically tailor PAPR reduction techniques to the current conditions and the behavior of users, adapting to changing traffic loads. By combining ML with high-end technologies such as massive MIMO and millimeter-wave communications, more reductions in PAPR can be achieved [51], thus optimizing the performance of the system and using the spectrum more efficiently. ML can take advantage of the capabilities offered by these future networks, so that it is able to optimize PAPR reduction in the different layers of communication and achieve efficient resource allocation and throughput.

VI. CONCLUSION

The paper offers a comprehensive overview of machine learning (ML)-based techniques to mitigate Peak-to-Average Power Ratio (PAPR) in Orthogonal Frequency Division Multiplexing (OFDM) systems. The emergence of wireless technologies and the evolution towards fifth generation 5G and upcoming sixth generation 6G networks have greatly emphasized the need for more effective PAPR reduction techniques. Although existing techniques such as Clipping and Filtering, Partial Transmit Sequence (PTS) and Selected Mapping (SLM) provide a certain level of relief, they come with performance degradation and are not suitable for next-generation systems. ML techniques, on the other hand, such as supervised-learning (ANNs, DNNs), unsupervised learning (K-Means clustering), and reinforcement learning (Q-Learning, Deep Q-Networks), can be applied, which offer optimal alternatives for dynamic PAPR reduction. But the large and diverse datasets required, model interpretability, and real-time computational constraints still present major challenges. While most of the current literature only covered a relatively narrow set of ML algorithms, the field is progressing towards having hybrid ML models, federated learning models that would perform over distributed networks, and low-latency and real time models. Moreover, the combination of ML-based PAPR reduction techniques with emerging communication technologies, including massive MIMO and millimeter-wave communications, may facilitate efficient resource allocation, improved system throughput, and better spectrum utilization. In conclusion, the integration of ML techniques for PAPR minimization will be a crucial aspect in the development of the more intelligent, energy-saving, and scalable communication systems for the coming 5G and beyond era.

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