

A Proactive Machine Learning Based Neural-Chaos Architecture For Physical Layer Security Through PAPR Reduction

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Abstract- Proactive physical layer security has evolved with the emergence of Web 3.0 which shifts control from centralized cloud servers toward distributed edge nodes, blockchain miners/validators, and peer-to-peer communication. Many of these nodes rely on low-power radios and operate in highly dynamic environments. One of the most pressing challenges is to implement proactive security through Peak to Average Power Ratio (PAPR) reduction. PAPR reduction techniques such as clipping, selective mapping, and tone reservation ensure that edge devices handle OFDM waveforms efficiently, allowing decentralized nodes to participate reliably in consensus protocols and data exchange without frequent downtime or excessive energy consumption. One of the major challenges that multiplexed data suffers from is high value of PAPR which make data transmission perceptible. The proposed work uses a neural selective mapping (N-SLM) technique and attains lower PAPR compared to previously existing work, thereby increasing the security of distributed wireless networks.

Keywords: Machine Learning, Web 3.0, PAPR, N-SLM,, Companding, Interleaving, Bit Error Rate (BER).

I. INTRODUCTION

Proactive physical layer security is important to implement in wireless networks with the emergence of Web 3.0 and IoT and de-centralized networks.



Fig.1 Conceptual Framework for Web 3.0

The IoT and Web 3.0 is an ecosystem of connected physical objects that are accessible through the internet. Some applications of IoT are [2]:

- Smart Cities.
- Healthcare
- Transportation
- Traffic Control
- Manufacturing
- Large Scale Automation
- Big Data Applications etc.

The major challenges of IoT based systems are [3]:

- Increasing number of users, so need for more bandwidth.
- Limited Bandwidth availability.
- One of the techniques to address the above problems is using Orthogonal Frequency Division Multiplexing (OFDM) in IoT Based Systems [4].

Security is a foundational requirement of Web 3.0, and physical-layer enhancements complement blockchain-based trust mechanisms. High PAPR signals can produce nonlinear distortion that leaks side information and weakens

confidentiality. By reducing PAPR, the transmitted waveform becomes less predictable and less prone to amplifier-induced leakage [5]. Techniques like Partial Transmit Sequence and SLM inherently add pseudorandom features to the signal, creating an additional physical-layer security layer. This aligns with Web 3.0's philosophy of trustless communication, where security is ensured through protocol design and signal-level robustness rather than centralized control [6].

II. PAPR AND SECURITY

Web 3.0 extends blockchain participation beyond servers to mobile devices, drones, sensors, and AR/VR endpoints. These devices often perform crypto operations, wallet authentication, and peer-to-peer data exchange [7]. High PAPR not only increases energy consumption but also introduces side-channel vulnerabilities related to power fluctuations. PAPR reduction stabilizes the device's power profile, reduces EM leakage, and protects crypto keys or blockchain transactions against power-analysis attacks. This is particularly important for lightweight blockchain clients and IoT nodes that require long battery life and secure local processing. Orthogonal Frequency Division Multiplexing or OFDM is a technique that works on the principle of orthogonality [8]. The carriers or signals are mutually orthogonal and hence create no overlap. Using OFDM in place of FDM helps in accommodating more users or devices in the same available bandwidth [9].

The major advantages of this technique are high spectral efficiency and efficient digital implementation. The drawback lies in the fact that the amplitude variations of OFDM signals is large, which requires large back-off in the transmitter amplifier and hence High Power Amplifiers (HPAs) are not efficiently used. In order to reduce the distortion caused by a HPA without setting it to large back-offs, several techniques have been introduced that limit the peak of the envelope of the signal (clipping) a problem that is usually referred to as peak-to-average power ratio (PAPR) reduction. These techniques have varying PAPR-reduction capabilities, power, and bandwidth and complexity requirements. PAPR is a very well-known measure of the envelope fluctuations of a multicarrier (MC) signal and plays a decisive role in the adoption of any particular technique. So the major problem with OFDM is high peak to power ratio or PAPR [10].

Web 3.0 applications such as metaverse platforms, real-time holographic communication, and immersive AR/VR demand high throughput and ultra-low latency [11]. High PAPR can cause nonlinear distortion in the RF chain, leading to constellation warping, increased BER, and degraded

visual/audio quality. PAPR reduction ensures smooth transmission of high-bandwidth multimedia streams without amplifier clipping. It allows metaverse devices, wearable displays, and haptic interfaces to maintain consistent Quality of Experience (QoE), which is crucial for user immersion in decentralized virtual environments [12].

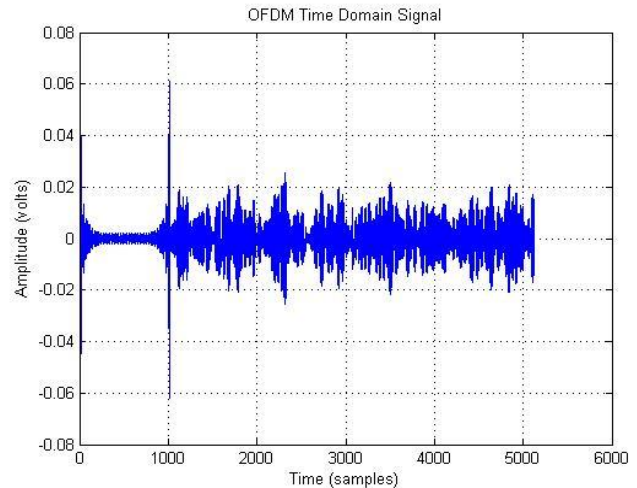


Fig.2 Time Domain Data Stream

The graph above shows the time domain OFDM signal. It can be seen that the signal has high peaks leading to high peak to average power ratio defined by [13]:

$$PAPR = \max \{x^2(t)\} / \text{mean}\{x^2(t)\} \quad (1)$$

Where $x(t)$ denotes the time domain OFDM signal.

The Complementary Cumulative Distribution Function (CCDF) is often used to analyze the magnitude of PAPR in an OFDM system, which is mathematically defined as [14]:

$$\text{Probability (PAPR } \{x\} > Y) = 1 - (1 - e^{-Y})^N \quad (2)$$

Here N is the number of sub-carriers,

Y is any arbitrary value of PAPR above which the possibility of attaining PAPR is evaluated. The CCDF plot clearly indicates the possibility of attaining PAPR greater than a particular PAPR value. Since the user data is random in nature, hence the modulated version of the OFDM signal is also random in nature. Hence probabilistic approaches need to be used for the analysis of PAPR [15].

III. SELECTIVE MAPPING

Selective mapping is the most fundamental and highly efficient technique to reduce PAPR. It provides a high performance as compared to normal OFDM. In this method set of m different symbols are generated of the same signal X

and out of these m symbols the symbol with minimum PAPR is transmitted, which is given by [16]:

$$\text{Min}\{\text{PAPR}(x(t)^m)\} \quad (3)$$

The block diagram of the SLM technique is given below [17]:

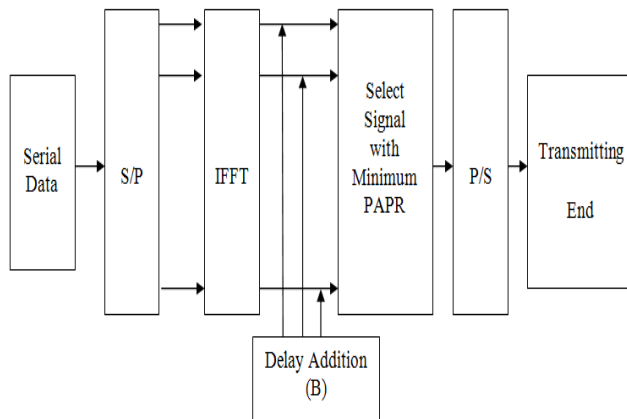


Fig.3 Block Diagram of SLM Technique

The only disadvantage of SLM can be thought to be the increase in complexity in case more delay vectors are added which eventually increases the searching complexity [18]. Each X block contains a wide variety of binary information, and those blocks are improved by means of one-of-a-kind phase sequence [19]. These exclusive segment collections are termed as M . After multiplying with M distinctive stages a very changed information movement is acquired [20]. This changed statistics circulation is implemented to the IDFT block which generates mutually orthogonal subcarriers and those subcarriers are modulated via the records movement. Without the IDFT blocks, N nearby oscillators could be wanted for generating N together orthogonal subcarriers which might in turn boom the complexity and electricity consumption of the gadget whilst making it cumbersome. The larger the wide variety of levels introduced, i.e. the bigger the period of the segment vector, extra is the PAPR discount capability [21].

IV. NEURAL SLM (N-SLM)

Various neural network architectures have been employed to optimize the SLM process. Feedforward Neural Networks (FNNs), Deep Neural Networks (DNNs), Convolutional Neural Networks (CNNs), and Long Short-Term Memory (LSTM) networks are commonly used depending on system requirements. Traditional SLM works by generating multiple statistically independent phase-rotated

versions of the same data block and selecting the one with the lowest PAPR for transmission. While effective, classical SLM suffers from two major drawbacks: high computational complexity due to multiple IFFT operations and the need to transmit side information that informs the receiver about the chosen candidate sequence. This side information, if corrupted or lost, can severely impact data recovery. Furthermore, generating many candidate signals increases processing time and energy consumption, making conventional SLM less suitable for delay-sensitive or low-power devices [22].

To overcome these limitations, researchers have developed hybrid SLM techniques, which combine SLM with other complementary strategies such as Partial Transmit Sequence (PTS), clipping, precoding transforms, and optimization heuristics. These hybrid approaches aim to enhance PAPR reduction while simultaneously lowering computational load and minimizing side-information overhead. By merging the strengths of multiple approaches, hybrid SLM techniques achieve an improved trade-off between complexity, performance, and implementation cost [23].

These algorithms intelligently explore the space of phase rotation vectors, reducing the number of candidate signals needed while finding near-optimal PAPR solutions. Compared to random phase selection in classical SLM, heuristic-enhanced SLM achieves lower PAPR with fewer iterations, making it attractive for real-time deployment [24]. Another direction in hybrid SLM research focuses on side-information-free approaches. These techniques integrate SLM with special constellation mapping strategies, differential encoding, or look-up-table-based phase sequences that allow the receiver to implicitly infer the chosen SLM candidate without explicit side information. This eliminates vulnerability to SI errors and enhances system reliability, especially in fading and low-SNR environments. Such methods are highly relevant for secure wireless networks, where minimizing overhead reduces the chance of eavesdropping and improves throughput [25].

In modern wireless systems such as 6G NR, WiFi-6/7, vehicular communication, and future 6G waveforms, the need for efficient PAPR reduction continues to grow due to higher bandwidths, massive MIMO, and energy-sensitive devices. Hybrid SLM techniques offer a scalable and flexible solution that adapts to system requirements—whether low complexity, security, BER performance, or latency reduction is prioritized. Their modular nature allows designers to blend multiple schemes, optimizing performance under diverse channel environments and hardware constraints. In the proposed selective mapping technique, the signal received

after the selective mapping technique is analysed and residual peaks are found. The residual peaks are multiplied with an inverse sync function so as to reduce the residual peaks [25].

The neural network is trained using large datasets consisting of OFDM input symbols, corresponding phase sequences, and measured PAPR values. During training, the network learns the relationship between the transmitted data and the optimal phase sequence. Once trained, the network can rapidly predict the best phase sequence for new OFDM symbols without evaluating every possible candidate.

The hybrid Neural Network-based SLM technique begins by generating a set of candidate phase sequences. Instead of applying all phase sequences and calculating their corresponding PAPRs, the neural network evaluates the input data and predicts the most promising phase sequence. Only the predicted candidates undergo IFFT processing, after which the signal with the lowest PAPR is selected for transmission. This intelligent filtering mechanism substantially reduces computational effort while maintaining effective PAPR reduction. The receiver processes the transmitted signal similarly to conventional SLM using side information or appropriate decoding methods [26].

Training Process:

The performance of the Neural Network depends heavily on the quality of its training. Large simulation datasets are generated by transmitting numerous OFDM frames under different modulation schemes such as QPSK, 16-QAM, or 64-QAM. Each frame is processed using conventional SLM to determine the optimal phase sequence and the corresponding PAPR value. These labeled datasets serve as training examples for supervised learning. The network adjusts its weights using optimization algorithms such as Bayesian Regularization, Adam, or Levenberg-Marquardt until the prediction error is minimized. After successful training, the model generalizes well to unseen OFDM symbols [27].

One of the most significant benefits of combining Neural Networks with SLM is the reduction in computational complexity. Conventional SLM requires multiple IFFT operations proportional to the number of candidate phase sequences. Since IFFT computation dominates the processing time, reducing the number of candidate evaluations considerably lowers computational requirements. Neural Networks perform inference very quickly after training, allowing real-time prediction of optimal phase sequences with minimal processing overhead. This makes the hybrid approach suitable for high-speed wireless communication systems.

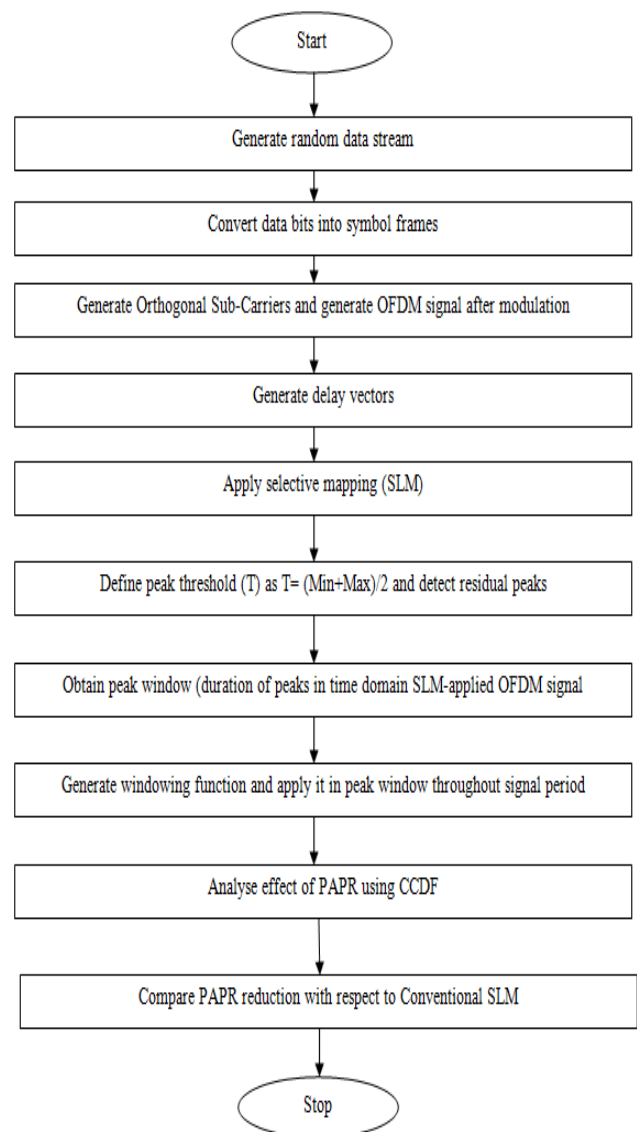


Fig.4 Flowchart of Proposed Technique

In the proposed scheme, an inverse sync window is multiplied with the residual peaks of the signal after SLM is applied. The inverted sync is chosen since it resembles the inverted peaks of a typical time domain OFDM signal. The inverted sync function is defined as:

$$W=1-\text{sinc}(m)/\pi^2.m^2 \quad (5)$$

The inverted sync function is shown in the figure below:

With increasing number of phase vectors, the search complexity remains the major challenge in this case. The further reduction of the PAPR can be done based on the

windowing function used in conjugation with the SLM approach.

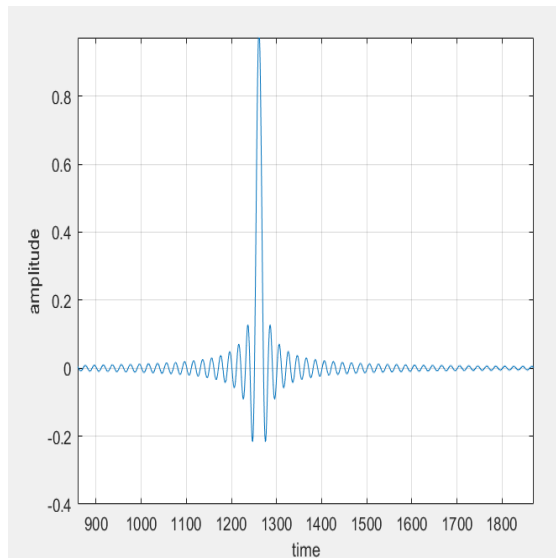


Fig.5 Implementing the sync window

Figure 5 depicts the sync window that is to be inverted and applied to the residual peaks. While other windowing functions could be used, the one with the similarity with the actual data streams after modulation has been chosen.

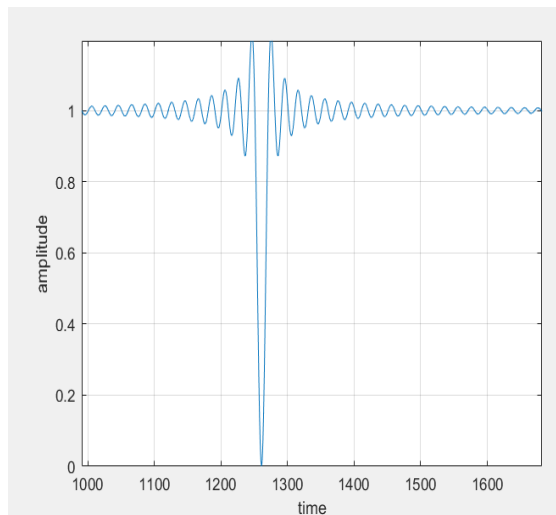


Fig.6 Implementing the inverted sync window

Figure 6 depicts the inverted sync window implemented on residual peaks of the SLM.

Hybrid NN-SLM techniques generally achieve PAPR reduction performance comparable to or slightly better than conventional SLM. Because the neural network learns complex relationships between input data and phase sequences, it often predicts candidates that produce lower

PAPR than random selection. Simulation studies have demonstrated that Neural Network-assisted SLM achieves significant PAPR reduction while maintaining signal integrity. The Complementary Cumulative Distribution Function (CCDF), commonly used for evaluating PAPR performance, shows noticeable improvement compared with traditional OFDM transmission.

V. RESULTS

The results are analyzed using the CCDF curve and an earlier plummet or fall in the CCDF curve among two systems indicates that the PAPR has been reduced in the one with an earlier fall of CCDF or PAPR.

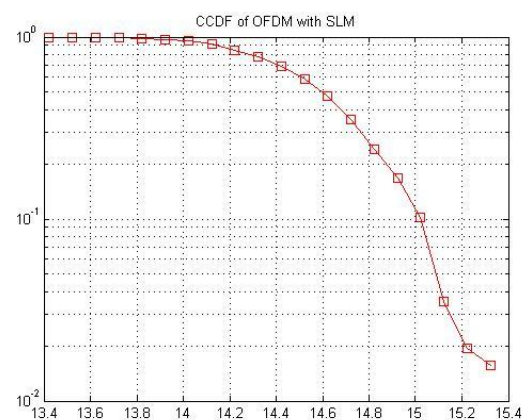


Fig.7 CCDF of Conventional SLM

Figure 7 depicts the PAPR cdf for the conventional version of the SLM algorithm which attains a PAPR of 15.4.

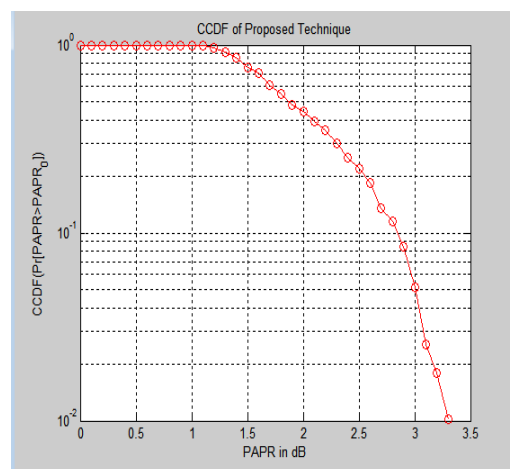


Fig.8 CCDF Proposed Technique

Figure 8 depicts the PAPR cdf for the proposed PAPR reduction approach which attains a PAPR of almost 3.5. Thus the proposed approach attains an much lesser PAR compared to baseline SLM.

A comparison with existing work, i.e. Elahi et al., [10] reveals that the approach by Elahi et al. attains a PAPR of 9Db which is significantly higher than the proposed work.

VI. CONCLUSION

The integration of Neural Networks with Selective Mapping offers several important advantages. It significantly reduces computational complexity by minimizing the number of IFFT operations. It achieves effective PAPR reduction without introducing signal distortion. The method preserves BER performance while improving amplifier efficiency. Neural Networks provide fast decision-making once trained, enabling real-time implementation. By improving power efficiency, securing physical-layer communication, supporting decentralized edge nodes, and enhancing QoS for immersive applications, PAPR reduction connects the physical wireless infrastructure with the decentralized philosophies of Web 3.0. As future networks transition into 6G with native blockchain integration, metaverse services, and distributed AI, PAPR-optimized waveforms will remain fundamental to achieving reliability, sustainability, communication in next-generation digital ecosystems. A modification to the selective mapping technique has been proposed so as to reduce the PAPR of the system. The CCDF has been used for the analysis of the PAPR of the system. It can be seen from the results that the proposed system attains extremely low values of PAPR in comparison to previous baseline approaches thereby increasing system security.

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