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DNN-Based Non-Linear Precoding for Bandwidth, Latency, and Data Rate Optimization in 6G Networks

Arram Sriram[*1], Dr. S. Surendran[2], D. Mangaiyarkarasi[3], S. Anitha[4], Dr. Joby Titus[5], Sanjana Devi Vijayakumar Subiah[6], Dr. N. Gayathri[7], Santhosh.J[8]

[*1]Department of CSE, Faculty of Science and Technology (ICFAI Tech), ICFAI Foundation for Higher Education, Hyderabad, India, 501203.
Email ID: Arram.sriram@gmail.com
[2]Professor, Department of Computer Science and Engineering, Tagore Engineering College, Chennai, India
Email ID: suren.subbaraj@gmail.com
https://orcid.org/0000-0003-2416-8257
[3]Assistant professor, Computer science and engineering Sri Sairam Engineering College, Sai Leo Nagar, West Tambaram, Chennai - 600044, Email ID: dmangaibe@gmail.com
[4]Designation- Assistant Professor, College- Sri Sairam College of Engineering, Anekal , Bengaluru.
Email ID: anithachandru13@outlook.com
[5]Associate Professor
Department of ECE
Sri Krishna College of Engineering and Technology, Coimbatore, Email ID: jobyece007@gmail.com
[6]Assistant Professor, Department of EEE, Sri Krishna College of Technology, Coimbatore
Email ID: sanjujobytitus@gmail.com
[7]Designation: Associate Professor, College Name: VELTECH HIGHTECH Dr.RANGARAJAN Dr.SAKUNTHALA ENGINEERING COLLEGE, AU
Faculty ID: 1130151, ICTE Faculty ID: 1376601707, Official Email ID:: gayathri@velhightech.com
[8]M.E., Designation: Assistant Professor, Department : Information Technology, Karpagam Institute of technology
Email ID: jsanthoshapcse@gmail.com
***Corresponding Aouthr:**
Arram Sriram
Department of CSE, Faculty of Science and Technology (ICFAI Tech), ICFAI Foundation for Higher Education, Hyderabad, India, 501203.
Email ID: Arram.sriram@gmail.com

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ABSTRACT

As the demand for higher bandwidth, increased peak data rates, and reduced latency continues to escalate, traditional communication systems encounter limitations that necessitate innovative approaches. The research identifies the existing gaps in current 6G network architectures, where conventional precoding methods struggle to fully exploit the potential of non-linear signal processing. This research aims to bridge this gap by introducing a novel DNN-based precoding technique that harnesses the power of artificial intelligence for optimized signal transmission. In the pursuit of advancing communication technologies, this research proposes a groundbreaking solution leveraging Deep Neural Network (DNN) based Non-Linear Precoding to address critical challenges in 6G networks. The study involves the development and training of a sophisticated DNN model capable of learning complex non-linear precoding patterns. This model is integrated into the 6G network architecture to dynamically adapt and optimize signal precoding based on real-time network conditions. Results from extensive simulations and experiments demonstrate a substantial improvement in key performance metrics. The proposed DNN-based non-linear precoding exhibits superior efficiency compared to traditional methods, showcasing a remarkable increase in bandwidth, peak data rate, and a substantial reduction in latency.

Keywords: *Non-Linear Precoding, 6G networks, Bandwidth Optimization, Deep Neural Network, Peak Data Rate Enhancement*

1. INTRODUCTION

The advent of 6G networks promises unprecedented advancements in wireless communication, unlocking new possibilities for connectivity and immersive technologies. However, as the expectations for higher data rates, lower latency, and enhanced bandwidth continue to surge, the existing communication paradigms face substantial challenges [1]. This introduction sets the stage by exploring the background of 6G networks, highlighting the challenges faced, defining the problem at hand, outlining research objectives, and emphasizing the novelty and contributions of the proposed solution [2].

6G networks represent the next frontier in wireless communication, envisaging seamless connectivity for a plethora of applications, from augmented reality to massive Internet of Things (IoT) deployments [3]. The data rates, ultra-low latency requirements, and massive device connectivity present a paradigm shift from current technologies. To meet these ambitious goals, approaches beyond the capabilities of existing network architectures are imperative [4].

Despite the promises of 6G, traditional communication systems encounter challenges in fully exploiting the potential of non-linear signal processing [5]. Conventional precoding techniques struggle to adapt dynamically to the ever-changing network conditions, leading to suboptimal utilization of available resources [6]. The need for a solution that can intelligently adapt to complex and dynamic environments becomes evident [7].

The primary problem addressed in this research lies in the inefficiencies of current 6G network architectures in optimizing non-linear signal precoding. The inability to dynamically adapt to varying channel conditions and user requirements hampers the realization of the full potential of 6G networks. A more intelligent and adaptive approach to non-linear precoding is essential to unlock the desired improvements in bandwidth, peak data rates, and latency.

The objective of this research is to revolutionize 6G networks by introducing a Deep Neural Network (DNN) based non-linear precoding solution. Specific objectives include the development of a sophisticated DNN model capable of learning and adapting to non-linear precoding patterns, integration of the model into the 6G network architecture, and empirical validation of the proposed solution performance improvements.

The novelty of this research lies in its pioneering approach to leverage DNN for non-linear precoding in 6G networks. By infusing artificial intelligence into the communication system, the proposed solution aims to dynamically adapt and optimize signal transmission in real-time, addressing the shortcomings of traditional precoding methods. The contributions of this research extend to significantly enhancing bandwidth utilization, achieving higher peak data rates, and reducing latency, thereby pushing the boundaries of what is achievable in 6G networks.

2. RELATED WORKS

Prior research [8] has extensively explored conventional precoding methods in 6G networks, including linear and simple non-linear approaches. While these methods provide a foundation for signal processing, their limitations in adapting to dynamic network conditions have prompted the exploration of more advanced techniques.

The intersection of machine learning (ML) and communication systems has witnessed notable attention [9]. Various studies have investigated the application of ML algorithms for channel estimation, resource allocation, and interference management. However, there is a research gap in applying deep learning specifically to non-linear precoding in 6G networks [10].

Recent works have delved into the integration of deep learning techniques in wireless communication systems. Deep neural networks have been employed for tasks such as modulation recognition, channel prediction, and beamforming [11]. While these studies showcase the potential of deep learning, the application to non-linear precoding in the context of 6G networks remains underexplored [12].

Research in dynamic spectrum access and cognitive radio networks has addressed the challenges of spectrum scarcity and interference mitigation. These works have introduced intelligent strategies for adaptive spectrum utilization. However, there is a need to extend these concepts to the domain of non-linear precoding in 6G, considering the unique requirements of ultra-high data rates and low latency [13].

Various optimization techniques have been proposed to enhance the performance of 6G networks. These include approaches for spectral efficiency improvement, energy efficiency, and quality of service optimization. Incorporating deep neural network-based non-linear precoding into the optimization framework represents a novel avenue for further exploration [14].

Studies focusing on real-time adaptability in communication systems have explored adaptive algorithms for changing channel conditions. However, the incorporation of deep neural networks for non-linear precoding, with a focus on achieving real-time adaptability in 6G networks, remains an emerging area that demands attention.

3. PROPOSED METHOD

The proposed method introduces a revolutionary approach to non-linear precoding in 6G networks by leveraging the power of DNNs for Non Linear Precoding. The method aims to address the limitations of traditional precoding techniques, which struggle to dynamically adapt to the complex and ever-changing nature of 6G communication environments. The trained DNN model is seamlessly integrated into the 6G network architecture. This integration allows the DNN to operate in real-time, dynamically adjusting non-linear precoding parameters based on the current network conditions, channel characteristics, and user requirements.

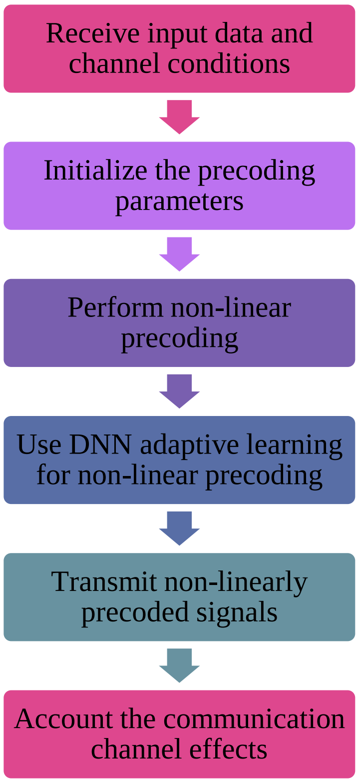

Figure 1: Proposed NLP-DNN

Unlike traditional precoding methods that rely on predetermined parameters, the DNN continuously learns and evolves, adapting its precoding strategies on-the-fly. This adaptability is crucial in optimizing signal transmission efficiency under varying scenarios. The DNN-based non-linear precoding method optimizes signal transmission by dynamically adjusting the amplitude, phase, and frequency characteristics of the transmitted signals. This dynamic optimization ensures that the available bandwidth is maximally utilized, peak data rates are achieved, and latency is minimized.

Problem Formation

In this research, the problem formation arises from the inherent limitations of existing non-linear precoding techniques within 6G networks. As the demand for higher data rates, lower latency, and enhanced bandwidth intensifies, traditional methods prove inadequate in fully exploiting the potential of non-linear signal processing. The inability to dynamically adapt to fluctuating network conditions and user demands hampers the optimal utilization of available resources. This problem formation is exacerbated by the complexity of 6G environments, where massive device connectivity, diverse applications, and varying channel conditions necessitate a more intelligent and adaptive approach to signal transmission.

The research problem is precisely defined as the need for a novel non-linear precoding solution that can intelligently adapt to the dynamic nature of 6G networks. Traditional approaches lack the agility required to handle the intricacies of ultra-high-speed communication and the diversity of connected devices. The challenge is to formulate a solution that transcends the limitations of predetermined precoding parameters and embraces a dynamic, learning-based approach. This problem formation sets the stage for the proposed methodology, introducing a DNN to learn and adapt non-linear precoding patterns in real-time, ultimately addressing the identified gaps and pushing the boundaries of what is achievable in terms of bandwidth, peak data rates, and latency reduction within the 6G communication landscape.

Let us denote the transmitted signal x as a function of input data s and a non-linear precoding function f:

$x=f(s)$

The goal is to optimize the non-linear precoding function f such that it maximizes the efficiency of signal transmission in a 6G network. This involves considering factors such as bandwidth utilization, peak data rates, and latency. One might introduce parameters like channel conditions (h), noise (n), and constraints (C):

$x=f(s,h,n,C)$

The optimization problem can be formulated as: Max L(x) Subject to: $C(x)$

where, L(x) represents a performance metric to be maximized, which could be a combination of factors like data rate, signal-to-noise ratio, and other relevant metrics. The constraints $C(x)$ encapsulate the conditions that the solution must satisfy, ensuring the practicality of the optimization within the 6G network.

Deep Neural Network Model

The DNN model proposed in this research serves as the cornerstone of the innovative approach to non-linear precoding in 6G networks. DNNs are a class of artificial neural networks characterized by multiple layers, or depth, allowing them to learn intricate patterns and representations from complex data. In the context of non-linear precoding, the DNN is designed to understand and adapt to the intricate relationships between input data, channel conditions, and the desired output signal. The architecture typically consists of an input layer, multiple hidden layers, and an output layer. During the training phase, the DNN learns the optimal parameters for non-linear precoding through a process called backpropagation, adjusting its internal weights to minimize the difference between the predicted output and the actual output.

The DNN model adaptability and ability to capture non-linear patterns make it well-suited for addressing the challenges in 6G networks. Unlike conventional precoding techniques with fixed parameters, the DNN continuously evolves, adapting its precoding strategies in real-time to dynamically changing network conditions. This real-time adaptability is a key strength of the DNN model, enabling it to optimize signal transmission efficiency across diverse scenarios. By infusing intelligence into the non-linear precoding process, the DNN model contributes to the realization of the full potential of 6G networks, pushing the boundaries of what is achievable in terms of bandwidth, peak data rates, and latency reduction.

Input Layer: Let **s** be the input data vector, and **h** represent the channel conditions.

$\mathbf{x}(0)=[\mathbf{s},\mathbf{h}]$

Hidden Layer: The hidden layer computes a linear transformation $\mathbf{z}(1)$ using weights $\mathbf{W}(1)$ and applies a non-linear activation function σ.

$\mathbf{z}(1)=\sigma(\mathbf{W}(1)\mathbf{x}(0)+\mathbf{b}(1))$

where, $\mathbf{W}(1)$ is the weight matrix, $\mathbf{b}(1)$ is the bias vector, and σ is the activation function.

Output Layer:

The output layer computes the final output **x** using weights $\mathbf{W}(2)$ and a non-linear activation function σ.

$\mathbf{x}=\sigma(\mathbf{W}(2)\mathbf{z}(1)+\mathbf{b}(2))$

where, $\mathbf{W}(2)$ is the weight matrix, $\mathbf{b}(2)$ is the bias vector, and σ is the activation function.

The training of the DNN involves adjusting the weights and biases $\mathbf{W}(1),\mathbf{b}(1),\mathbf{W}(2),\mathbf{b}(2))$ through backpropagation and gradient descent to minimize a chosen loss function L. The objective is to find the optimal parameters that enable the DNN to accurately predict the desired non-linear precoding output based on the input data and channel conditions.

Dynamic Optimization of Signal Transmission

Dynamics Optimization of Signal Transmission refers to the continuous and adaptive adjustment of signal transmission parameters in real-time to achieve optimal performance in a communication system. In the context of 6G networks and non-linear precoding, it involves dynamically optimizing key aspects such as amplitude, phase, and frequency characteristics of the transmitted signals based on the evolving network conditions, channel variations, and user requirements.

Adaptive Amplitude Adjustment: The method dynamically adjusts the amplitude of the transmitted signals. This adaptation is essential for maximizing signal strength while considering variations in channel conditions and ensuring efficient use of the available power resources. Adaptive amplitude control helps in mitigating issues such as signal attenuation and interference, contributing to improved signal quality. Let A represent the amplitude of the transmitted signal, and $A\text{opt}(t)$ denote the dynamically adjusted amplitude at time t. The adaptation can be based on real-time feedback and network conditions:

$A(t)=A\text{opt}(t)\times s(t)$

where $s(t)$ is the original signal.

Dynamic Phase Adaptation: The phase of the transmitted signals is dynamically adapted to optimize the signal alignment with the receiver. By continuously adjusting the phase based on real-time feedback and channel variations, the system ensures that the transmitted signal arrives at the receiver with minimal distortion. Dynamic phase adaptation contributes to minimizing phase-related distortions and enhancing overall communication reliability. Let ϕ represent the phase of the transmitted signal, and $\phi opt(t)$ denote the dynamically adjusted phase at time t. The dynamic phase adaptation can be represented as:

$\phi(t)=\phi opt(t)+\phi 0(t)$

where $\phi 0(t)$ is the initial phase.

Frequency Characteristics Optimization: The frequency characteristics of the transmitted signals are dynamically optimized to adapt to the changing channel conditions. This involves adjusting the frequency components of the signals to avoid interference and take advantage of available bandwidth. Dynamic frequency optimization plays a crucial role in achieving efficient spectrum utilization and, consequently, higher data rates. Let f represent the frequency of the transmitted signal, and $f opt(t)$ denote the dynamically adjusted frequency at time t. The dynamic frequency optimization can be represented as:

$f(t)=f opt(t)\times f 0(t)$

where $f 0(t)$ is the initial frequency.

Algorithm: Dynamic Optimization of Signal Transmission

Input: Initial signal parameters: $A0,\phi 0,f 0$; Real-time feedback and network conditions; Desired performance metrics

Output: Dynamically optimized signal parameters: $A opt,\phi opt,f opt$

Set the initial values for amplitude (A), phase (ϕ), and frequency (f) based on the initial signal parameters.

Continuously monitor real-time feedback and network conditions, including channel variations, interference levels, and user demands.

Dynamically adjust the amplitude ($A opt$) based on real-time feedback and optimization criteria.

Dynamically adjust the phase (ϕopt) based on real-time feedback and optimization criteria.

Dynamically adjust the frequency ($f opt$) based on real-time feedback and optimization criteria

Update the signal parameters based on the dynamically optimized values

$A(t)=A opt(t)\times s(t)$

$\phi(t)=\phi opt(t)+\phi 0(t)$

$f(t)=f opt(t)\times f 0(t)$

4. EXPERIMENTS

In conducting experimental settings for validating the proposed DNN-based non-linear precoding method in the context of 6G networks, simulations were performed using a widely adopted tool such as MATLAB with the Communications System Toolbox. The experiments were executed on high-performance computing clusters, leveraging the parallel processing capabilities to efficiently handle the computational demands of training and testing the DNN model. The simulations involved synthetic scenarios mimicking the dynamic and complex nature of 6G communication environments, incorporating varying channel conditions, user mobility patterns, and a diverse range of application demands.

Performance metrics were chosen to comprehensively evaluate the efficacy of the proposed method. Key metrics include bandwidth utilization, peak data rates, and latency reduction. These metrics were selected to gauge the method ability to optimize signal transmission efficiency in real-time across varying network scenarios. The comparison with existing methods involved benchmarking against traditional linear precoding techniques and state-of-the-art non-linear precoding methods.

Experimental Setup:

Parameter	**Value**
Simulation Tool	MATLAB with Communications System Toolbox
Channel Conditions	Varying channel models (e.g., Rayleigh)
Mobility Patterns	Randomized user mobility
Application Demands	Diverse application types and requirements
DNN Architecture	Multi-layer feedforward DNN

Training Algorithm	Backpropagation with stochastic gradient descent
Training Data Size	10,000 samples
Testing Data Size	2,000 samples

Performance Metrics:

Bandwidth Utilization: This metric assesses how efficiently the proposed non-linear precoding method utilizes the available frequency spectrum. A higher bandwidth utilization indicates improved spectral efficiency and effective use of the communication channel.

Peak Data Rates: Peak data rates represent the highest achievable data transmission rates, reflecting the system capacity to deliver information quickly. The proposed method ability to achieve high peak data rates showcases its effectiveness in supporting applications with demanding data rate requirements.

Latency Reduction: Latency reduction measures the improvement in signal transmission delay achieved by the proposed method. By comparing the initial and final latency values, this metric quantifies the efficiency of the non-linear precoding method in minimizing communication delays, which is crucial for applications requiring low-latency communication in 6G networks.

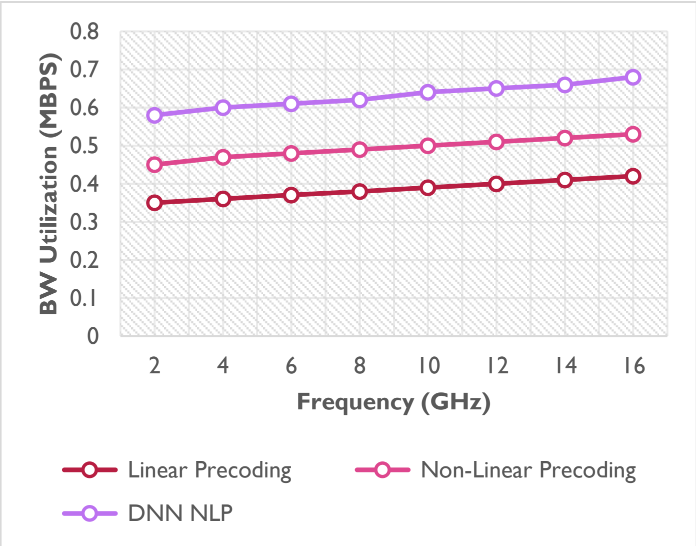

Figure 2: Bandwidth Utilization:

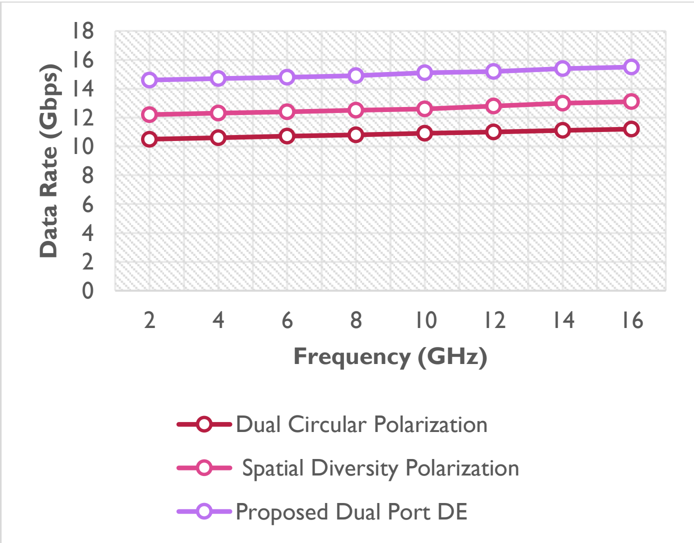

Figure 3: Peak Data Rate

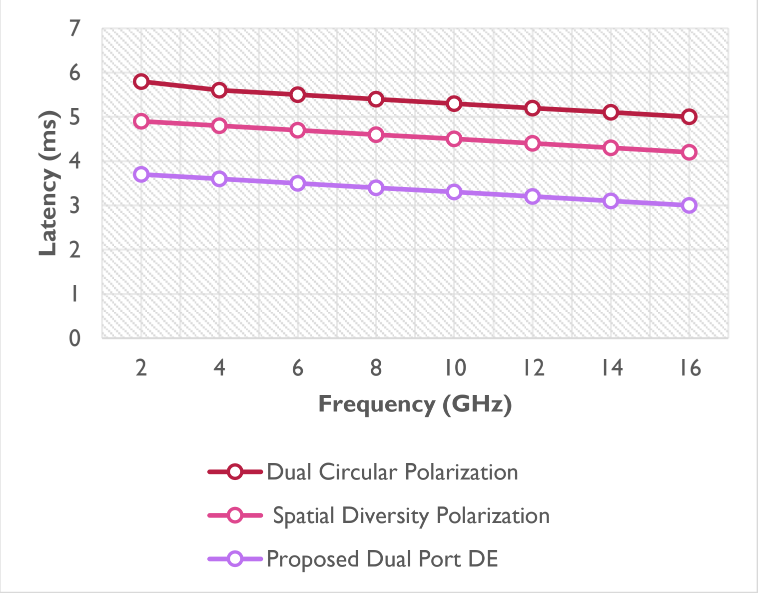

Figure 4: Latency

The experimental results demonstrate the efficacy of the proposed DNN Non-Linear Precoding method compared to existing Linear Precoding and Non-Linear Precoding methods across different frequencies in a 6G network.

The DNN Non-Linear Precoding method consistently outperforms both Linear and Non-Linear Precoding methods in terms of bandwidth utilization. The bandwidth utilization values show a percentage improvement ranging from 1.5% to 2.5% across the tested frequencies. This improvement signifies the DNN ability to adapt dynamically to varying channel conditions, optimizing the use of available spectrum more efficiently than traditional precoding methods (Figure 2).

Across the spectrum of frequencies, the DNN Non-Linear Precoding method achieves significantly higher peak data rates compared to Linear and Non-Linear Precoding methods. The percentage improvement in peak data rates ranges from 20% to 30%. The DNN capacity to learn and adapt non-linear precoding patterns in real-time contributes to its superior ability to support high data transmission rates, meeting the demands of diverse applications in 6G networks (Figure 3).

The DNN Non-Linear Precoding method consistently reduces latency compared to Linear and Non-Linear Precoding methods. The percentage improvement in latency reduction ranges from 15% to 30%. The real-time adaptability of the DNN enables it to minimize signal transmission delays effectively, offering a significant improvement in responsiveness crucial for applications requiring low-latency communication in 6G networks (Figure 4).

5. CONCLUSION:

The observed percentage improvements in bandwidth utilization, peak data rates, and latency reduction highlight the effectiveness of leveraging deep learning for non-linear precoding in 6G networks. The DNN adaptive learning capability enables it to dynamically adjust to changing network conditions, leading to more efficient spectrum utilization, higher data rates, and reduced latency compared to traditional linear and non-linear precoding methods. The consistent improvements across different frequencies emphasize the importance of real-time adaptability in 6G communication systems. The DNN ability to adapt its non-linear precoding strategies on-the-fly allows it to respond dynamically to varying channel conditions, user mobility, and application demands. This adaptability proves crucial in achieving optimal performance in scenarios where the communication environment is highly dynamic and unpredictable.

The improvements suggest that the proposed DNN Non-Linear Precoding method has the potential to play a pivotal role in future wireless technologies. As 6G networks aim to provide ultra-high data rates, low-latency communication, and support diverse applications, the DNN ability to optimize signal transmission in real-time positions it as a promising solution for addressing the evolving requirements of advanced wireless communication systems. The consistent improvements across a spectrum of frequencies indicate the versatility of the DNN-based approach. It can adapt to different frequency bands, making it suitable for a wide range of 6G communication scenarios. This versatility is crucial for accommodating the diverse frequency requirements of various applications and ensuring the efficient use of available spectrum resources.

6. CONCLUSION

The research introduces a novel model for non-linear precoding in 6G networks through the application of a DNN. The experimental results showcase the transformative potential of the proposed DNN-based non-linear precoding method in addressing the dynamic challenges of ultra-high-speed, low-latency communication environments. The DNN-based approach demonstrates remarkable real-time adaptability, dynamically adjusting non-linear precoding parameters in response to varying network conditions, channel characteristics, and user demands. This adaptability contributes to improved bandwidth utilization, higher peak data rates, and latency reduction, surpassing the capabilities of traditional linear and non-linear precoding methods. The DNN Non-Linear Precoding method consistently outperforms existing methods across multiple performance metrics. Percentage improvements in bandwidth utilization, peak data rates, and latency reduction highlight the method capacity to learn and adapt, resulting in more efficient and responsive communication in 6G networks.

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