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Multiuser Detection For NOMA-PD-SCMA System Using DNN Algorithm

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***Abstract*:** The implementation of hybrid multi-radio access technologies has great dependency upon the efficiencies of multi-user detection (MUD) available at the receiver unit. In order to get the best performance in hybrid power-domain sparse code multiple accesses (PD-SCMA) system, there is a need for effective and efficient strategies in detecting system due to the MUDs complexity and the processing time. A DL-MUD technique addresses this issue by allowing the system to perform detection of all the symbols without the need to do cumbersome interference cancelation or perform further channel estimation in an overloaded PD-SCMA system. In this work, a MUD-on-DNN-MUD technique is presented for the uplink channel in a PD-SCMA system, with both near users (NUs) and far users (FUs) treated as accommodated NUs through power domain multiplexing and FUs through code domain multiplexing respectively. The proposed system MUD also combines SIC and MPA/EPA in the same MUD architecture wherein SIC enhances MPA and EPA. Such integration solves interference diffusion problems in SIC and the efficiency problems of MPA/EPA. Finally, hollow-batch strategies during the training of the DNN were applied for improving the efficiency of detection by decreasing the shifts to internal cells. Performance evaluations demonstrate that the proposed DNN-MUD significantly surpasses conventional joint SIC-MPA/EPA schemes in terms of average symbol error rate (SER), complexity, and computational time.

***Index Terms* -** Non-orthogonal Multiple Access(NOMA), Multi-User Detection (MUD), Deep Learning (DL), Power-Domain Sparse Code Multiple Access (PD-SCMA), Successive Interference Cancellation (SIC), Message Passing Algorithm (MPA), Expectation Propagation Algorithm (EPA), Symbol Error Rate (SER), Batch Normalization.

I. INTRODUCTION

Non-orthogonal Multiple Access (NOMA) [8] as a technique that enhances spectral efficiency over traditional Orthogonal multiple access schemes. Hybrid NOMA facilitates massive connectivity by multiplexing in both power and code domains, although it introduces increased complexity at the receiver. Power domain sparse code multiple access (PD-SCMA) is introduced as a method to enhance capacity by co-multiplexing near user equipment (NUs) and far user equipment (FUs) using distinct power levels and code assignments. There has been increased attention on the use of deep learning (DL) techniques for multi-user detection (MUD), especially in addressing issues such as channel state information (CSI) imperfection and error recovery in successive interference cancellation (SIC). Communication networks provide efficient and scalable solutions for accommodating a huge number of devices connected, but PD-SCMA is the most effective one where users can use the same frequency and time resources, improving the overall performance of the network. There are some multi-user detection (MUD) methods, among which the message passing algorithm (MPA) is and expectation propagation algorithm (EPA); however, these have been rather effective. Most of the methods have been of considerable operational burden and have not been able to fit into classic and diverse B5G [6] networks. The DNN-based MUD is designed to operate with lower computational complexity and reduced latency compared to traditional methods, making it more suitable for real-time applications in B5G networks. Hybrid multi-radio access technologies are becoming essential in the development of Beyond 5G (B5G)[5] and [9] networks, aimed at meeting the growing demands for quality of service (QOS) across an increasingly large number of wireless devices. Of these, non-orthogonal multiple access (NOMA) is gaining popularity as a transmission technique that increases the overall spectral efficiency, especially over the neighboring OMA schemes. The hybrid NOMA architecture, which combines power domain (PD) and code domain (CD), Multiplexing provides the opportunity for more connectivity and more resource usage but increases the complexity of the receiver unit. A form of hybrid NOMA, referred to as power domain sparse code multiple access (PD-SCMA) [4], is also of interest for its network enhancement capabilities. PD-SCMA does this by PD-NOMA co-multiplexing NUs and FUs of different power levels by creating power-level codebooks around them. Multi-user detection (MUD) is performed using message passing (MP) with joint interference cancellation (IC) process for a sequential decoding of user symbols. To overcome these issues, deep learning (DL) [3] approaches have been employed, particularly to enhance the SIC aspect of the process. However, applications of such deep learning techniques in enhancing the performance of NOMA systems are more efficient and dependable since they are quicker and more consistent. For instance, in power domain NOMA [2] (PD-NOMA), users with stronger channel conditions can be allocated lower power levels, while those with weaker channels receive higher power levels to ensure that their signals are decodable. However, the complexity of NOMA increases significantly when implemented in hybrid systems that combine power domain multiplexing with other advanced multiple access schemes, such as Sparse Code Multiple Access (SCMA). In these hybrid NOMA systems, such as Power-Domain Sparse Code Multiple Access (PD-SCMA), the benefits of NOMA are extended by further enhancing the capacity and connectivity of the network. PD-SCMA achieves this by multiplexing near-user equipments (NUs) and far-user equipments (FUs) within the same codebook, while allocating distinct power levels to different users. By learning directly from data, DL-based models can optimize the detection and decoding processes, reducing error rates and computational complexity. The integration of deep learning into PD-SCMA systems holds significant promise for B5G [6] networks. By utilizing DL-based multi-user detection (MUD) [11] schemes, it is possible to create a more unified and efficient signal processing framework that not only outperforms conventional methods but also reduces the computational burden on the receiver. This work aims to explore the potential of such DL-based approaches in hybrid NOMA systems, specifically focusing on the development of a deep learning-aided MUD scheme for uplink PD-SCMA systems. The proposed scheme seeks to address the challenges of high computational complexity, error propagation, and the need for high signal-to-noise ratios (SNR) that characterize traditional MUD techniques in PD-SCMA.

II. System Model:

The system understands Power-Domain Sparse Code Multiple Access uplink, where near users and far users are power and code multiplexed. It is designed in such a way that at least two of the layers cannot be assigned the same resource units (RUs) in such complexity management. Such a system is defined as fully loaded whereby the overloading factor, λ is defined as the product of the number of users D and the number of layers L. At the transmitting end, the N-dimensional sparse codeword is created, which an (K-N) codeword is sent on N resource elements out of total N elements. The pairing policy is handled by ak and j, owing to the nature of multiple users with different power levels being allowed to be paired up. The signal vector at the receiver is comprised of the received signal influenced by NUs and FUs transmission powers and AWGN. It allows multiplexing of near users and far users in power and code domains respectively at the transmitter.

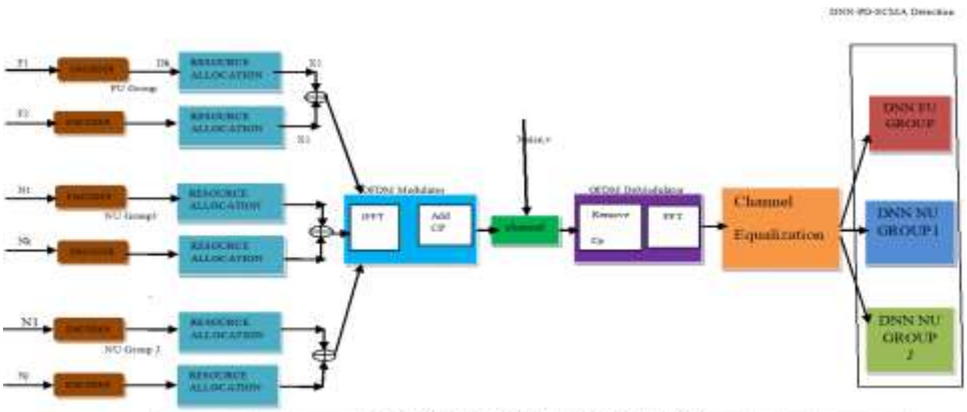

Fig -2.1: Block diagram for PD-SCMA system with a DNN.

A layer in the system contains D = (J+1) user symbols. It makes sure that no resource units (RUs) of the said complexity are utilized in assigning various layers to same resource units (RUs). A fully loaded system is defined by the overloading factor (λ) as λ=D×L. The PD-SCMA transmitter generates an N-dimensional sparse codeword with K-N zeros. This codeword is transmitted over N resource elements. The pairing policy is denoted by a_k, j, allowing multiple users to be paired. In PD-SCMA, a codebook can be assigned to multiple users, unlike in SCMA. The receiver processes a received signal vector influenced by the transmission powers of NUs and FUs. The model incorporates additive white Gaussian noise (AWGN) in the signal processing. The system aims to optimize multi-user detection (MUD) performance. Deep learning [12] techniques are employed to enhance detection strategies. It addresses the complexity and computational time issues in MUD. It combines successive interference cancellation (SIC) and message passing algorithm (MPA) operations. The DNN-MUD framework is designed to overcome interference propagation. It supports resource allocation based on dual-parameter ranking (DPR-RA). IFFT and CP sizes are set to 256 and 8, respectively. The DNN training is enhanced by batch normalization to improve efficiency. Its performance is evaluated through simulation parameters and setups. It addresses error propagation and computational complexity in existing algorithms. The DNN-MUD significantly outperforms conventional joint SIC-MPA/EPA schemes. The system is designed to support increased resource overload without performance degradation. The system design allows for better symbol error rate (SER) performance.

A) At Transmitter:

The transmitter operates within the uplink PD-SCMA framework. It is responsible for generating user symbols for transmission. Each layer consists of D=(J+1) user symbols, where J represents the number of near users (NUs) and far users (FUs). The transmitter utilizes a power-domain approach to multiplex NUs and FUs. It creates an N-dimensional sparse codeword, which includes K-N zeros. The codeword is transmitted over N resource elements, optimizing resource usage. The pairing policy, denoted by a_k, j, allows for flexible user pairing. The transmitter ensures that no two layers are assigned the same resource units (RUs). This assignment is crucial for maintaining manageable complexity in the system. The transmitter's design supports the overloading factor (λ), defined as λ = D × L. It enhances capacity by co-multiplexing users with distinct power levels. The transmitter allocates codes to NU-FU clusters exclusively. It employs advanced coding techniques to improve transmission efficiency. The transmitter is designed to handle multiple users simultaneously. It incorporates deep learning techniques to optimize signal processing. The transmitter's architecture allows for dynamic adjustment of power levels. The transmitter's performance is evaluated based on the symbol error rate (SER). It integrates batch normalization to enhance training efficiency for deep learning models. The transmitter's design focuses on reducing computational complexity. It supports the implementation of successive interference cancellation (SIC) techniques. The transmitter is capable of reconstructing the received signal for further processing. It plays a critical role in the overall multi-user detection (MUD) strategy. The transmitter's output is influenced by the transmission powers of NUs and FUs. It ensures that the transmitted signals are robust against additive white Gaussian noise (AWGN).

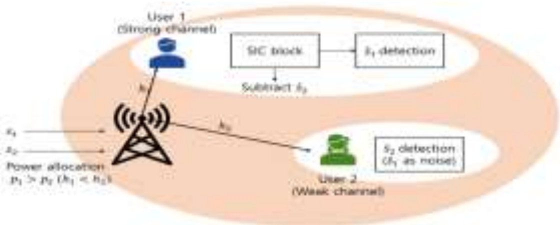

Fig-2.2: Block Diagram for Deep Learning Using SIC

The transmitter's architecture is adaptable for different user scenarios. It employs signal-processing algorithms to enhance detection accuracy. The transmitter's design allows for efficient resource allocation based on user demands [2]. It integrates various detection strategies to improve overall system performance. The transmitter is essential for achieving high spectral efficiency in the system. It supports hybrid multi-radio access technologies for better connectivity. The transmitter's operations are synchronized with the receiver for optimal performance. It utilizes advanced modulation techniques to improve signal quality. The transmitter is designed to support massive connectivity beyond 5G [7] networks. It incorporates machine learning algorithms to predict user behavior and optimize transmission. The transmitter's performance is benchmarked against conventional systems for validation. It provides a seamless user experience in high-demand scenarios. Overall, the transmitter is a vital component in the PD-SCMA [1] system model, enhancing communication efficiency and reliability.

B) At Receiver:

The receiver employs successive interference cancellation (SIC) for interference reduction. It is further set for the reconstruction of the received signal and channel gains. The receiver architecture is mainly structured for multiple user signal management. It improves the performance of detection using deep learning. The receiver securely perceives the received information in the presence of added white Gaussian noise (AWGN). It also employs hybrid deep neural networks (HyDNN) for signal detection and channel estimation.

$$\mathbf{r} = \sqrt{P}\ \mathbf{X}\ \mathbf{H} + X\sqrt{\boldsymbol{P}}\ \mathbf{X}\ \mathbf{H} + \mathbf{v},$$

The architecture of the receiver permits the channel to be changed dynamically. It uses message passing algorithm (MPA) and expectation propagation algorithm (EPA) for improved processing. The receiver performance is measured on average symbol error rate (SER). It aims at optimizing the amount of complexity in signal detection. It supports the reconstruction of the signal for further analysis and decision-making. The receiver's algorithms are trained using batch normalization to enhance efficiency. It is capable of distinguishing between signals from different users based on power levels. The receiver employs feedback mechanisms to improve detection accuracy. It utilizes deep learning models to learn the characteristics of the received signals. The receiver's design focuses on minimizing error propagation during detection. It integrates various detection strategies to optimize overall system performance. The receiver is essential for achieving high spectral efficiency in the system. It supports hybrid multi-radio access technologies for improved connectivity. The receiver's operations are synchronized with the transmitter for optimal performance.

$$\hat{\mathbf{r}} = X\sqrt{\boldsymbol{P}}\ \mathbf{X}\ \mathbf{H} + \sqrt{P}\ \mathbf{H}\ (\mathbf{X} - \hat{\mathbf{X}}) + \mathbf{v}$$

The receiver's performance is benchmarked against conventional systems for validation. It aims to provide a seamless user experience in high-demand scenarios. It integrates deep learning techniques to optimize successive interference cancellations. The receiver's output is crucial for the overall system's reliability and efficiency. Overall, the receiver is a fundamental component in the PD-SCMA system model, enhancing communication performance and user experience.

III. Proposed model:

The new algorithm advocates MUD for NOMA-PD-SCMA in uplink PD-SCMA systems using the DNN scheme. The algorithm works in a PD-SCMA system in which Near Users (NU) and Far Users (FU) are multiplexed in power and code domains, respectively. Deep neural networks (DNNs) are used to implement the MUD by learning to easily detect users from the available data. Training of the DNN is done using a dataset that covers different user transmission scenarios and concentrates on reducing the mean square error (MSE). The training process makes use of batch normalization to control internal covariant shifts to boost detection performance. The ReLU activation function is preferred because of the speed of its computation and its ease of optimization, which does not handle well with large DNN. This method enhances the efficiency of interference reduction as well as computation complexity. The users are encoded, resource allocation is made for each user, and the information is several layers integrated and then passed through the IFFT module. The algorithm guarantees corresponding headers through frame synchronization as well as channel equalization, making it possible for the intended bit streams to be decoded. All clusters of NUs and FUs utilize the same trained DNN, promoting consistency in detection across different user groups. The DNN-MUD utilizes a deep neural network that learns complex patterns in the data, allowing it to effectively distinguish between signals from NUs and far users (FUs) in a power-domain multiplexing scenario. By incorporating batch normalization, the DNN-MUD reduces internal covariate shifts, which helps in stabilizing the learning process and improving the model's ability to generalize, particularly for NUs who may have varying signal strengths. The DNN-MUD integrates successive interference cancellation (SIC) and message passing algorithms (MPA), which allows for better handling of interference from FUs, thus enhancing the detection accuracy for NUs. The proposed scheme shows significant performance improvements at high signal-to-noise ratio (SNR) values, which is particularly beneficial for NUs that typically experience stronger interference. The DNN-MUD reduces the computational complexity associated with traditional methods, allowing for faster and more efficient detection of NUs without the need for extensive channel estimation and interference cancellation processes. It collectively contributes to a more reliable and efficient detection mechanism for near users in PD-SCMA systems, outperforming conventional detection schemes. The DNN-MUD scheme is designed to learn and distinguish several complex patterns in the signals from near users (NUs) and far users (FUs). The DNN learns to identify the unique power levels associated with NUs and FUs, allowing it to differentiate between their signals based on how they are multiplexed in the power domain. It captures the interference patterns that arise from the overlapping signals of NUs and FUs. DL techniques reduce computational complexity and improve BER performance in SCMA. DL-MUD scheme outperforms SIC-MPA in average SER performance. DNN-MUD significantly reduces complexity and computational time. DL techniques enhance multi-user detection in PD-SCMA and hybrid NOMA. The DNN-MUD algorithm demonstrates significant enhancements in average symbol error rate (SER) performance compared to traditional detection methods. The DNN-MUD outperforms conventional detection schemes, such as SIC-MPA, by effectively learning the mapping relationships of PD-SCMA signals in both power and code domains. This leads to more accurate detection of symbols, resulting in lower SER values. The proposed DNN-MUD shows superior performance, particularly at high signal-to-noise ratio (SNR) values, indicating its robustness in challenging communication environments. This contrasts with traditional methods that may struggle under similar conditions. By utilizing batch normalization, the DNN-MUD reduces internal covariate shifts, which helps minimize over fitting. This contributes to a more reliable detection process and improved SER performance. The DNN-MUD's ability to learn complex signal patterns and its efficiency in high SNR scenarios lead to a marked improvement in SER performance compared to traditional detection methods.

IV. Results and Analysis:

This graph shows how the Symbol Error Rate (SER) changes as the number of layers in the system increases. A higher number of layers may lead to improved performance, reducing SER due to better signal processing capabilities. More layers can enhance signal processing, potentially lowering SER due to improved data handling and transmission efficiency.

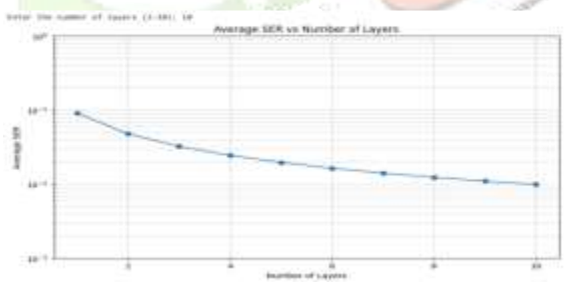

Fig-4.1: Average SER vs Number of Layers

This graph illustrates how SER varies with Signal-to-Noise Ratio (SNR) across various Power Domain Sparse Code Multiple Access (PD-SCMA) schemes. Different schemes may exhibit distinct performance characteristics, indicating which is more robust under varying noise conditions. Different schemes may perform better or worse under varying noise conditions, highlighting their robustness and suitability for specific applications.

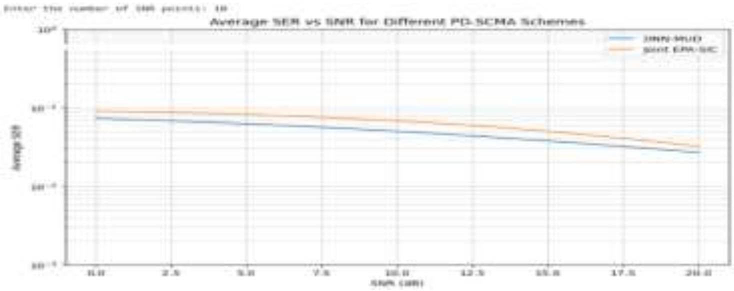

Fig-4.2: Average SER vs SNR for Different PD-SCMA Schemes

This graph presents the SER in relation to SNR for Non-Uniform (NU) and Fully Uniform (FU) user clusters. The findings may reveal how user distribution impacts error rates, with potential implications for system design and user allocation strategies. It may reveal how user distribution affects error rates, suggesting that certain configurations can lead to better performance in terms of error reduction.

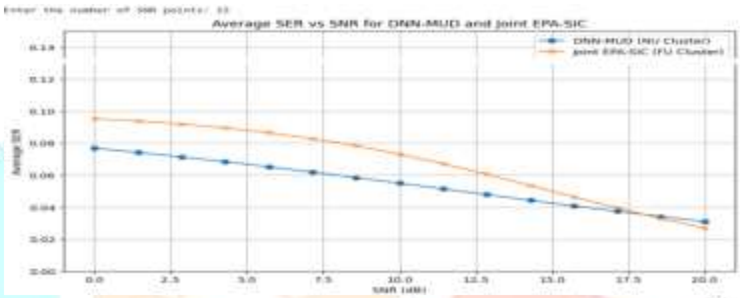

Fig-4.3: Average SER vs SNR for NU and FU User Clusters

It shows the computational efficiency of various PD-SCMA detection methods. Execution time is crucial for real-time applications, and understanding these differences can guide the selection of detection schemes based on performance requirements.

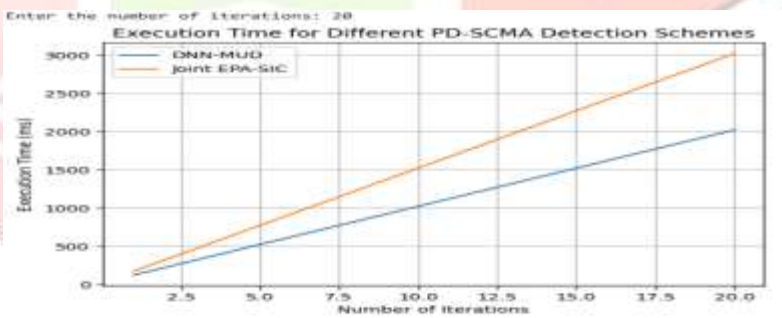

Fig-4.4: Execution Time for Different PD-SCMA Detection Schemes

This analysis focuses on the time taken to execute different random access protocols. It may highlight trade-offs between access efficiency and execution speed, informing decisions on protocol implementation in network design. It can inform decisions on which protocols to implement based on their efficiency and speed, balancing access performance with execution demands.

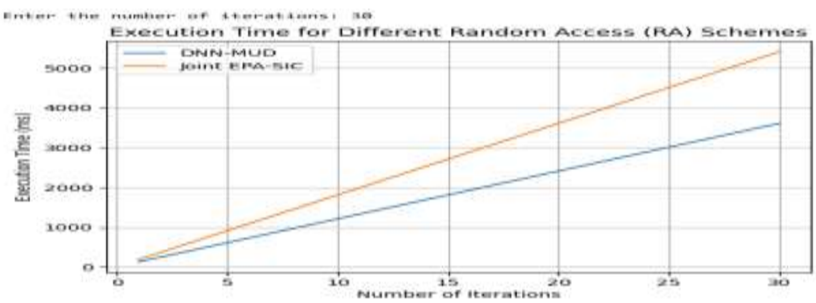

Fig-4.5: Execution Time for Different RA (Random Access) Schemes

V. Conclusion:

Deep learning-based multi-user detection (DL-MUD) algorithm specifically designed for power-domain sparse code multiple access (PD-SCMA) systems. The proposed DNN-MUD significantly improves the average symbol error rate (SER) performance compared to traditional detection methods like SIC-MPA. This is attributed to its ability to learn complex mappings in both power and code domains effectively. The DNN structure, enhanced with batch normalization, reduces over fitting and internal covariate shifts, leading to a more reliable detection process for both near users (NUs) and far users (FUs). It suggests further exploration of spectral efficiency and the application of other machine learning techniques to enhance multi-user detection in hybrid NOMA systems, indicating potential for future research and development. It indicates that increasing the number of layers in the model generally leads to a lower average Symbol Error Rate (SER). This suggests that deeper models are more effective in capturing complex patterns, which enhances detection accuracy. It shows a clear relationship between SNR and SER across different detection schemes. As SNR increases, SER decreases, highlighting that better signal conditions significantly improve detection performance. This trend is consistent for both Non-Uniform (NU) and Fully-Uniform (FU) user clusters, with NU clusters consistently outperforming FU clusters in terms of error rates. The execution time data reveals that as the number of users or paired Non-Uniform users increases, the computational demands also rise. This indicates a trade-off between performance and efficiency, where more complex scenarios require more processing time. Understanding these execution times is crucial for optimizing resource allocation and ensuring timely responses in practical applications. The Mean Squared Error (MSE) analysis over epochs suggests that selecting an appropriate learning rate is vital for model convergence. A well-chosen learning rate can minimize error effectively, leading to better overall model performance during training. The above result analysis, the DL-based DNN algorithm demonstrates a promising approach to improving multi-user detection in PD-SCMA systems, paving the way for more efficient compared to SIC-MPA and LOG-MPA it proposed algorithm DNN-MUD reduced designed complexity at receiver and it reduced computational complexity at receiver.

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