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Enhancing Uplink Communication with Multi-User Detection in NOMA Through Deep Neural Networks

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Abstract- In the realm of wireless communication, Multi-user Detection (MUD) techniques have become crucial for ensuring efficient and reliable transmission in complex network scenarios. Particularly in the uplink channel of Non-Orthogonal Multiple Access (NOMA) systems, effective MUD approaches are essential to overcome interference and enhance overall performance. One innovative solution that has shown promise in addressing these challenges is the utilisation of Deep Neural Networks (DNNs) for MUD in grant-free NOMA uplink communications. By leveraging the power of artificial intelligence and machine learning, DNNs can effectively distinguish and decode signals from multiple users sharing the same frequency band in NOMA networks. By training deep learning algorithms on large datasets of multi-user signals, DNNs can learn complex patterns and correlations, enabling them to accurately separate and detect individual user signals in the presence of interference. This capability improves communication's overall reliability and efficiency in NOMA systems and opens up opportunities for enhancing spectral efficiency and capacity.

Keywords- NOMA, 5G Communication, Deep Learning, User Detection

I. INTRODUCTION

Uplink communication, which refers to data transmission from user devices to base stations, is crucial in wireless networks. However, it faces challenges such as limited bandwidth and interference from multiple users sharing the same resources. NOMA, an innovative multiple-access technique, addresses these challenges by allowing users to share the same time-frequency resources non-orthogonally, enabling simultaneous transmissions. Multi-User Detection (MUD) plays a pivotal role in NOMA systems by distinguishing and decoding signals from multiple users, thereby mitigating interference and improving overall system efficiency. Traditional MUD algorithms often rely on heuristic methods or suboptimal solutions, which may not fully exploit the potential gains offered by NOMA [1, 2, 3, 4].

On the other hand, deep Neural Networks (DNNs) have demonstrated remarkable capabilities in learning complex patterns from data [5,6]. By leveraging the power of deep learning, researchers aim to develop novel MUD algorithms tailored to the unique characteristics of NOMA systems. These DNN-based approaches have the potential to outperform traditional methods by adaptively adjusting to changing channel conditions and user dynamics. The proposed research explores the synergy between NOMA, MUD, and DNNs to enhance uplink communication performance. This exploration involves several key steps: Firstly, the development of a comprehensive system model that captures the dynamics of NOMA-based uplink communication, including channel fading, interference, and user diversity. Secondly, the design and training of deep neural network architectures optimised for multi-user detection in NOMA scenarios. This entails the generation of training data and the selection of appropriate network architectures and training algorithms. Extensive simulations or real-world experiments are needed to evaluate the performance of the proposed DNN-based MUD approach compared to traditional methods. Performance metrics such as bit error rate, throughput, and spectral efficiency will be analysed to assess the effectiveness of the proposed approach. The research findings will be discussed, highlighting the advantages and limitations of the proposed approach and outlining potential avenues for future research and practical deployment. Enhancing Uplink Communication with Multi-User Detection in NOMA Through Deep Neural Networks" represents a promising research direction that aims to leverage the capabilities of deep learning to optimise wireless communication systems, paving the way for more efficient and reliable uplink transmissions in NOMA-enabled networks. The remainder of the article delves into Section II, which introduces NOMA and deep learning; Section III explains the system model of NOMA; Section IV presents experimental analysis; and Section V is a conclusion.

II. NOMA DEEP LEARNING

Recent advancements in Deep Learning (DL) algorithms have revolutionised the field of wireless communications, particularly in handling heterogeneous data with intricate correlations, such as Channel State Information (CSI) [12]. Efficient training of DL models on such data has shown promising performance improvements. Within Non-Orthogonal Multiple Access (NOMA), DL has been extensively investigated in recent years, showcasing superior performance compared to traditional methods.

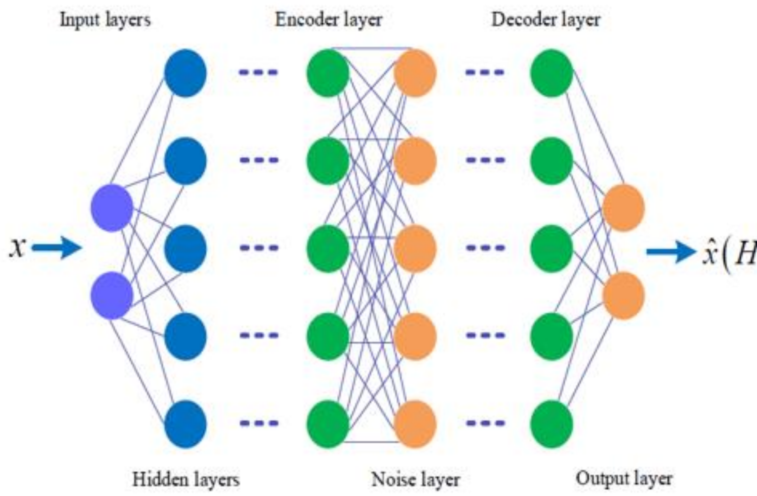

Figure 1. DL-based NOMA communication model

Three primary types of DL methods have emerged in the literature: supervised, unsupervised, and reinforcement learning. Supervised learning is commonly applied for CSI estimation and extends to spectrum sensing, localisation, and throughput prediction tasks. Unsupervised learning finds utility in user clustering and congestion control. Reinforcement learning, especially through algorithms like Q-learning, holds significant promise for resource management in wireless communication systems.DL finds application across various aspects of NOMA systems. It proves invaluable for processing complex data and achieving accurate CSI estimation. Training in NOMA systems can be categorised into offline and online methods. Offline training involves extensive training of input data using existing channel models, while online learning utilises real-time pilot signals for continuous adaptation. A DL-based NOMA model typically comprises hidden layers with multiple neurons, enabling robust training and recognition [13]. These hidden layers serve as memory components, retaining network states for tasks like dynamically fluctuating channel detection, as demonstrated in techniques such as long-short-term memory (LSTM) [14]. In NOMA systems, integrating both online and offline training methods facilitates auto-detection of CSI, ensuring adaptability to changing channel conditions [13]. DL techniques, like LSTM, leverage hidden layers to effectively process and retain preceding complex data, even under adverse weather conditions.

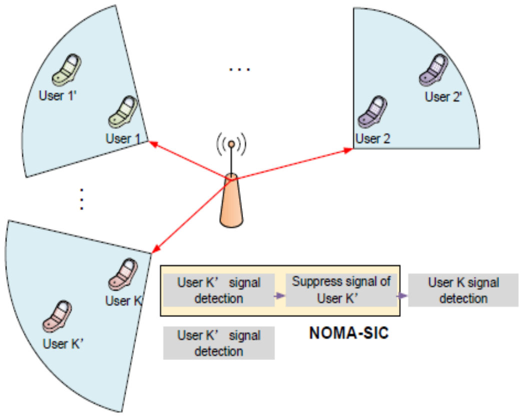

Figure 2. The system model of the NOMA system

III. SYSTEM MODEL

We examine a standard downlink Multiple-Input Multiple-Output Non-Orthogonal Multiple Access (MIMO-NOMA) configuration consisting of a single base station (BS) equipped with a uniform linear array (ULA) of M antennas, along with D multi-antenna users. The downlink channel operates under Rayleigh fading conditions, as depicted in Figure 2. Each user possesses Nr antennas, and the BS lacks specific information about each user link. In order to implement NOMA principles within the MIMO framework, users are randomly grouped into M clusters, each accommodating K users (resulting in D = KM). The multiplexing gain, capped at M when the BS hosts M antennas, determines the maximum number of clusters supportable without inter-cluster interference, denoted by M in this context [13, 14]. This study assumes Nr ≥ M [13] to circumvent the complexities associated with impractical beamforming vector allocation [16]. As outlined in [9, 13], the forthcoming 5G wireless networks are anticipated to feature ultra-dense deployment of small cells, resulting in a proliferation of low-power and cost-effective small-cell BSs. Therefore, it is reasonable to posit that such low-power BSs may be equipped with an equivalent or even fewer antennas than user equipment.

IV. EXPERIMENTAL ANALYSIS

This section provides numerical findings to evaluate the efficacy of our proposed deep learning-based joint resource allocation strategy for minimising total transmit power. We consider a scenario where the base station (BS) is centrally located within the cellular network. At the same time, user equipment (UE) is uniformly distributed within a circular area with a radius of 300 meters. Consequently, the distance between the BS and the kth UE denoted as dk, is randomly generated within the interval (0, 300). The system bandwidth is configured to B = 4 MHz, and the path-loss exponent β is set to 3.76, based on the typical 3GPP propagation environment [36].

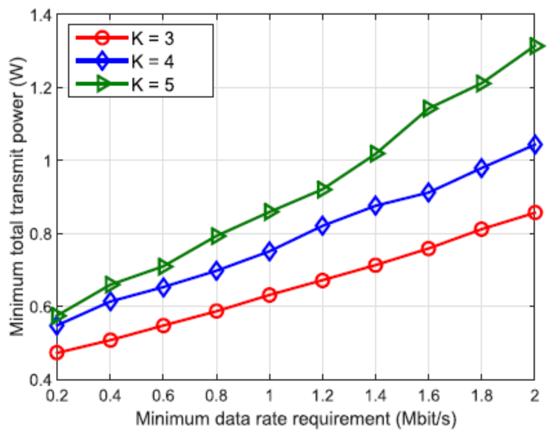

Figure 3. Comparison of minimum total transmit power of the proposed approach with different minimum data rate requirements.

Furthermore, we assume a power conversion efficiency (η) of 30% for energy harvesting (EH) circuits. Each UE is subjected to a minimum data rate requirement (Rreq) of 1 Mbit/s and a harvested power threshold (Ereq) of 0.1 W. Supplementary system parameters are adjusted by their respective simulation outcomes. To facilitate the construction, training, and execution of Deep Belief Networks (DBNs) within our proposed approach, we utilise the widely acclaimed Tensorflow r1.8 programming tool implemented on the Python 3.6.0 platform.

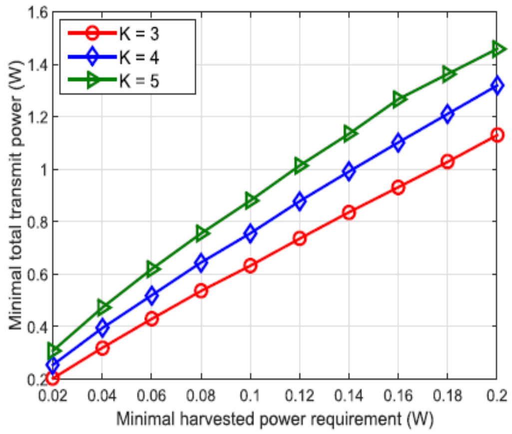

Figure 4. Comparison of minimum total transmit power of the proposed approach with different minimum harvested power requirements.

V. CONCLUSION

Due to its remarkable spectral efficiency and low-latency features, Non-Orthogonal Multiple Access (NOMA) is paramount in modern communication systems, particularly in 5G and beyond. Deep Learning (DL) stands poised to enhance NOMA's performance significantly. This study delves into the nuanced roles of DL methodologies across various NOMA applications, elucidating how DL techniques bolster NOMA's efficacy. Additionally, we outline the specific DL methods prevalent in the literature, detailing their respective functionalities. Finally, we engage in a brief discourse on potential avenues for future research within this domain. In particular, we focus on jointly optimising the characteristic pattern matrix, power allocation, and time-slot (TS) ratio assignment to minimise total transmit power while meeting Quality of Service (QoS) requirements and transmit power constraints. Due to integer variables and intra-band interference, the corresponding optimisation problem is non-convex and mixed-integer programming in its original form, making it extremely challenging to determine the optimal solution. To address this challenge, we have developed a deep learning-based approach comprising three phases: data preparation, model training, and solution execution.

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