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Department of Electrical Electronics Engineering

OPTIMUM BER IN NON-ORTHOGONAL MULTIPLE ACCESS FOR 5G WIRELESS TECHNOLOGY

Master Thesis

Aktham Hikmat Naser NASER

Supervisor

Asst. Prof. Dr. Halit YAHYA

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Turkish Abstract	**:**	Dik Olmayan Çoklu Erişim (NOMA), yüksek spektral verimlilik, azaltılmış gecikme süresi, arttırılmış güvenilirlik ve sağlam bağlantı sağlama potansiyeline sahip vaat edici bir teknolojidir. Bu, öncelikle optimal bit hata oranı (BER) performansının elde edilmesine odaklanmaktadır. Her bir zaman adımını ayrı bir alt taşıyıcı olarak ele alarak, birden fazla kullanıcı için mesajları etkili bir şekilde çözmek için tekrarlayan sinir ağları (RNN) kullanmaktadır. Ayrıca, verinin desenlerini otomatik olarak öğrenme yeteneğini kullanarak açık kanal tahmininin gereksiz olmasını sağlamak için derin

bir sinir ağı (DNN) kullanılmaktadır. Bu, geleneksel NOMA sistemlerinde mesajları çözme gibi görevlerde, alıcının işlemini basitleştirme ve hata yayılma etkilerini azaltma açısından avantajlıdır. Dikkatli simülasyonlar aracılığıyla, sistemin bit hata oranı (BER), eklenmiş beyaz Gauss gürültüsü (AWGN) ve Rayleigh dağılım sistemlerinde değişen sinyal-gürültü oranlarında değerlendirilir. Sonuçlar, DNN'nin en küçük kareler (LS), maksimum olabilirlik (ML) ve minimum ortalama kare hatası (MMSE) ile karşılaştırıldığında üstün BER performansı sergilediğini göstermektedir. Geniş SNR aralığına sahip bir QPSK demodülasyon şeması kullanılarak, DNN, iki kullanıcı için tüm sembol kombinasyonlarında LS, ML ve MMSE'ye kıyasla üstün BER performansı sergiler.

Anahtar Kelimeler: Dik Olmayan Çoklu Erişim (NOMA), 5G kablosuz teknolojisi, Bit Hata Oranı (BER), Tekrarlayan Sinir Ağı (RNN), Derin Sinir Ağı (DNN).

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DECLARATION

I hereby declare that in the preparation of this thesis, scientific ethical rules have been followed, the works of other persons have been referenced in accordance with the scientific norms if used, there is no falsification in the used data, any part of the thesis has not been submitted to this university or any other university as another thesis.

Aktham Hikmat Naser NASER

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The thesis study of Aktham Hikmat Naser NASER titled as **Optimum BER in Non-Orthogonal Multiple Access For 5G Wireless Technology** has been accepted as MASTER in the department of Electrical and Electronic Engineering by out jury.

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SUMMARY

Non-orthogonal multiple access (NOMA) is a promising technology that has the potential to deliver high spectral efficiency, reduced latency, improved reliability, and substantial connectivity. This primarily focuses on achieving optimal bit error rate (BER) performance. It utilizes recurrent neural networks (RNN) to efficiently decode messages for multiple users, treating each time step as a separate subcarrier. A deep neural network (DNN) is employed to eliminate the need for explicit channel estimation, leveraging its ability to autonomously learn patterns in data. This proves advantageous in tasks like decoding messages in traditional NOMA systems, simplifying the receiver's operation, and mitigating error propagation effects. Through careful simulation, the BER of the system is evaluated over varying signal-to-noise ratios (SNR) in additive white Gaussian noise (AWGN) and Rayleigh distribution systems. The results show that the DNN exhibits superior BER performance compared to least square (LS), maximum likelihood (ML), and minimum mean square error (MMSE). Utilizing a QPSK demodulation scheme with wide SNR range, the DNN exhibits superior BER performance compared to LS, ML, and MMSE across all symbol combinations for two users and for two tested cases of subcarrier pilot numbers with 16 & 64.

Keywords: Non-Orthogonal Multiple Access (NOMA), 5G wireless technology, Bit Error Rate (BER), Recurrent Neural Network (RNN), Deep Neural Network (DNN).

ÖZET

Dik Olmayan Çoklu Erişim (NOMA), yüksek spektral verimlilik, azaltılmış gecikme süresi, arttırılmış güvenilirlik ve sağlam bağlantı sağlama potansiyeline sahip vaat edici bir teknolojidir. Bu, öncelikle optimal bit hata oranı (BER) performansının elde edilmesine odaklanmaktadır. Her bir zaman adımını ayrı bir alt taşıyıcı olarak ele alarak, birden fazla kullanıcı için mesajları etkili bir şekilde çözmek için tekrarlayan sinir ağları (RNN) kullanmaktadır. Ayrıca, verinin desenlerini otomatik olarak öğrenme yeteneğini kullanarak açık kanal tahmininin gereksiz olmasını sağlamak için derin bir sinir ağı (DNN) kullanılmaktadır. Bu, geleneksel NOMA sistemlerinde mesajları çözme gibi görevlerde, alıcının işlemini basitleştirme ve hata yayılma etkilerini azaltma açısından avantajlıdır. Dikkatli simülasyonlar aracılığıyla, sistemin bit hata oranı (BER), eklenmiş beyaz Gauss gürültüsü (AWGN) ve Rayleigh dağılım sistemlerinde değişen sinyal-gürültü oranlarında değerlendirilir. Sonuçlar, DNN'nin en küçük kareler (LS), maksimum olabilirlik (ML) ve minimum ortalama kare hatası (MMSE) ile karşılaştırıldığında üstün BER performansı sergilediğini göstermektedir. Geniş SNR aralığına sahip bir QPSK demodülasyon şeması kullanılarak, DNN, iki kullanıcı için tüm sembol kombinasyonlarında LS, ML ve MMSE'ye kıyasla üstün BER performansı sergiler.

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ABBREDIVATIONS

1G : First Generation

2G : Second Generation

3G : Third Generation

4G : Fourth Generation

AWGN : Additive White Gaussian Noise

Bi-LSTM : Bi-directional long short-term memory

BS : Base Station

CD NOMA : Code Domain NOMA

CNN : Convolutional neuronal networks

CS : Compressive Sensing

CSI : Channel State Information

DL : Deep Learning

DNN : Deep Neural Network

FDMA : Frequency Division Multiple Access

LA : Large Area Synchronized Code Division Multiple Access

LDS OFMA : Low-Density Spreading OFDM

LDS-CDMA : Low-Density Spreading CDMA

LMDS : Local Multipoint Distribution Service

LS : Least square

LSTM : Long short-term memory

LTE : Multiple Access Technique

MC-CDMA : Multi-Carrier Code Division Multiple Access

MIMO : Multiple Input Multiple Output

ML : Maximum Likelihood

MMSE : Minimum mean square error

MRT : Maximum Ratio Transmission

MUSA : Multi-User Shared Access

NOMA : Non-Orthogonal Multiple Access

OFDM : Orthogonal frequency-division multiplexing

OFDMA : Orthogonal Frequency Division Multiple Access

OMA : Orthogonal Multiple Access

OP : Outage Probability

PD NOMA : Power Domain NOMA

PSC : Phase-Shift Configuration

RAT : Radio Access Technology

RIS : Reconfigurable Intelligent Surface

RMTC : Reconfigurable Multi Technology Core

RNN : Recursive Neural Network

SC- FDMA : Single Carrier Frequency Division Multiple Access

SCI : Successive Interference Cancellation

TAS : Telephone Answering System

TDMA : Time Division Multiple Access

UE : User Equipment

UWB : Ultra-wideband

WD NOMA : Waveform Domain NOMA

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PREFACE

Throughout the process of preparing and writing this thesis, I express my gratitude to **Asst. Prof. Dr. Halit Yahya** for the support rendered and to the members of the Thesis jury for their valuable comments and suggestions that assisted in managing and advancing the thesis. Last but not least, my sincere appreciation goes to my family for their support.

INTRODUCTION

The advent of 5G networks heralds a new era in wireless communication, marked by their ability to support a massive number of concurrent connections. This advancement unlocks a plethora of applications previously unattainable with older mobile network generations. From the Internet of Things (IoT) to augmented reality and virtual reality experiences, 5G empowers diverse innovations. Crucially, 5G networks offer low-latency communication, vital for applications like self-driving cars and remote surgery. Moreover, they promise higher data transfer rates and more reliable connections, even in areas with poor coverage. However, as 5G networks evolve to meet the demands of high-data-rate applications and low Bit Error Rates (BER), ensuring their safe and responsible development becomes paramount. Non-Orthogonal Multiple Access (NOMA) emerges as a promising solution to enhance 5G networks' efficiency and capacity.

In this work, we delve into NOMA, exploring its fundamental principles, distinguishing features, and various types. NOMA, as opposed to traditional Orthogonal Multiple Access (OMA) methods, allows for non-orthogonal resource allocation, boosting spectral efficiency and accommodating more users within a given bandwidth. By leveraging power and code domain multiplexing, NOMA optimizes resource allocation and enhances system performance.

In addition, it discusses the implementation of NOMA in practical scenarios, including its integration with Massive MIMO systems and addressing challenges such as inter-cell interference. Additionally, we explore other NOMA variants like Pattern-Division Multiple Access (PDMA) and Low-Density Spreading Code Division Multiple Access (LDS-CDMA), highlighting their unique advantages and applications.

Furthermore, studies include investigating the performance of NOMA systems using deep learning techniques, optimizing system parameters, and evaluating BER performance. By harnessing the power of deep learning, it can enhance the efficiency and reliability of NOMA systems, paving the way for their widespread adoption in future communication networks.

The thesis discusses the integration of Non-Orthogonal Multiple Access (NOMA) with Deep Learning (DL) techniques to enhance wireless communication systems, particularly in the context of 5G networks. NOMA, a radio access technology, surpasses traditional orthogonal

multiplexing methods by employing superposition coding and Successive Interference Cancellation (SIC), thus optimizing the downlink broadcast channel's capacity region. Recent research explores NOMA-DL, which combines NOMA with DL techniques like neural networks, to further improve wireless communication performance. NOMA-DL addresses challenges such as power allocation and channel estimation, promising significant enhancements in efficiency and capacity.

DL techniques, including Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and Long Short-Term Memory (LSTM) networks, are highlighted for their ability to handle complex wireless channels, optimize resource allocation, and improve signal detection. The text emphasizes the benefits of DL-enabled NOMA systems, such as increased throughput, reduced latency, and enhanced resource management. Real-world applications of NOMA-DL in 5G networks are discussed, showcasing its potential to enhance data transfer speeds, network efficiency, and capacity.

Additionally, the thesis reviews literature on NOMA-DL, illustrating how DL methodologies address challenges in NOMA systems and improve performance. The integration of NOMA with DL offers solutions to resource management, channel estimation, and signal detection problems, leading to improved wireless communication effectiveness.

The thesis also provides an overview of fifth-generation (5G) technology, highlighting its features such as high-speed transmission, enormous capacity, and cost-effectiveness. It discusses the role of Quality of Service (QoS) in 5G communication systems and emphasizes the importance of QoS for optimizing network performance.

Overall, the integration of NOMA with DL techniques presents a promising pathway for enhancing wireless communication systems, addressing challenges, and unlocking new capabilities in the era of 5G technology.

CHAPTER ONE

FUNDAMENTALS OF NOMA

1.1 Introduction to NOMA

One of the key features of 5G networks is their ability to support a massive number of concurrent connections (Mahmoud Aldababsa, et al, 2018). This enables a wide range of applications that were not possible with previous generations of mobile networks (M. Abd-Elnaby, et al, 2022). For example, the internet of things (IoT) will be able to support a huge number of connected devices, ranging from smart homes to autonomous vehicles. In addition, 5G networks will be able to support augmented reality and virtual reality applications, which will produce new forms of entertainment and communication (Asif, S., 2018; Condoluci, Massimo, et al, 2018). Another important feature of 5G networks is their ability to provide low-latency communication, this means that there will be less delay between sending a command and receiving a response, which will be particularly important for applications such as self-driving cars and remote surgery. 5G networks will also be able to support higher data transfer rates, leads to faster downloads and uploads of data, as well as more reliable connections in areas with poor coverage (Siriwardhana, Y., et al, 2021). As the 5G networks continue to evolve with growing demand for high data-rate applications and low BER, it should address concerns and ensure that 5G networks are developed in a safe and responsible manner (Onishi, Teruo, et al, 2020; Chowdhury, Mostafa Zaman, et al, 2020). Several NOMA approaches have been presented up to these points, the suggested NOMA types include power domain NOMA (PD-NOMA), code domain NOMA (CD-NOMA), sparse code multiple access (SCMA), pattern division multiple access (PDMA), multiuser shared access (MUSA), frequency domain NOMA (FD-NOMA), temporal domain NOMA (TD-NOMA), and hybrid NOMA (Nonaka, N., et al, 2014; Zhang, S., et al, 2017; Cai, Y., et al; 2018; Maatouk, A., et al, 2018; Caliskan, E., et al, 2018).

1.2 NOMA Features and Types

In traditional Orthogonal Multiple Access (OMA) methods, radio resources are assigned for the multiple users that may orthogonal in time, frequency, or coding domain. Because OMA allocates resources orthogonally, there should be no interference between numerous users. As a result, separating the signals of distinct users can be accomplished with a single-user detection approach. Theoretically, OMA is known to occasionally fall short of multiuser wireless networks' sum-rate capacities (Tse and Viswanath, 2005). In addition, the amount and scheduling detail of orthogonal resources determine the maximum number of supported users in standard OMA designs. To address the issues with OMA listed above, NOMA has recently been studied. Fundamentally, NOMA, illustrated in Figure 1, enables effective management of interferences through non-orthogonal resource allocation, accompanied by a moderate increase in receiver complexity. This innovative technique allows multiple users to share the same time-frequency resources, enhancing spectral efficiency and accommodating more users in a given bandwidth. The following are some of NOMA's primary benefits over OMA:

- Improved spectral efficiency
- Massive capacity and connectivity
- Low transmission latency and signaling cost
- Reliable communication

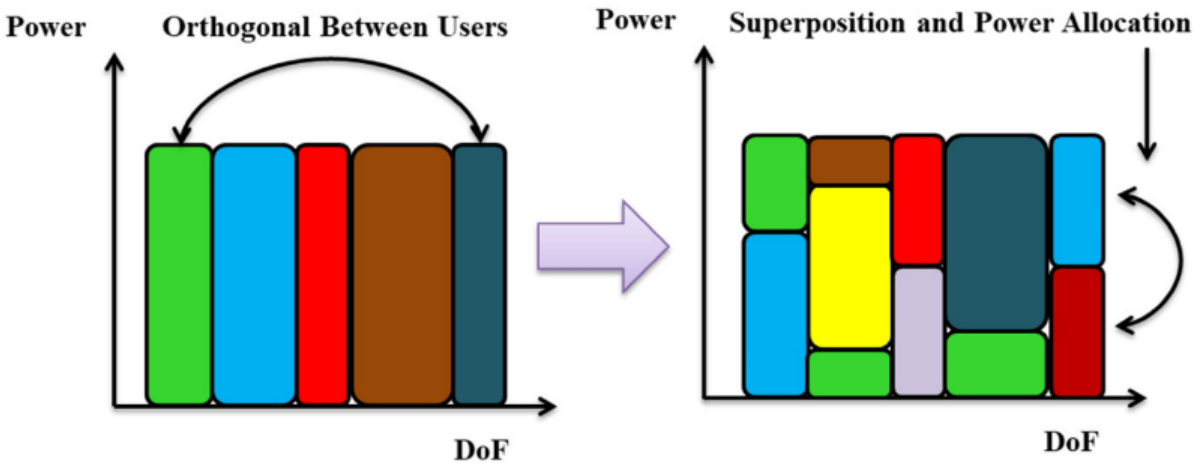

Figure 1. From OMA to NOMA by power domain multiplexing (Mohsan, S. A. H., et. al., 2023).

Two popular of dominating NOMA schemes can be identified:

- Power domain multiplexing,
- Code domain multiplexing,

To maximize and optimize system performance, power domain multiplexing is employed, allocating varying power levels to users according to their channel conditions. This approach is particularly beneficial in scenarios where successive interference cancellation (SIC) is commonly employed to mitigate multi-user interference. By allocating power strategically, users can be effectively separated. In downlink NOMA, as validated in (Ding, Lei, et al., 2017), exclusive utilization of power domain multiplexing is favored.

Code domain multiplexing (CDMA) or multicarrier CDMA (MC-CDMA), involves assigning unique codes to various users, who are subsequently multiplexed across the same time-frequency resources. Code domain multiplexing can accomplish specific spreading gain and shaping gain at the expense of greater signal bandwidth, which is how it differs from power domain multiplexing.

1.2.1 Power Assigning Multiplexing with NOMA

- NOMA with a SIC Receiver:

The major NOMA technique, utilizing power domain multiplexing and SIC receiver in the downlink, is depicted in Figure 2. Importantly, it's worth mentioning that this NOMA scheme can also be applied in the uplink, as demonstrated by (Hojeij et al., 2015).

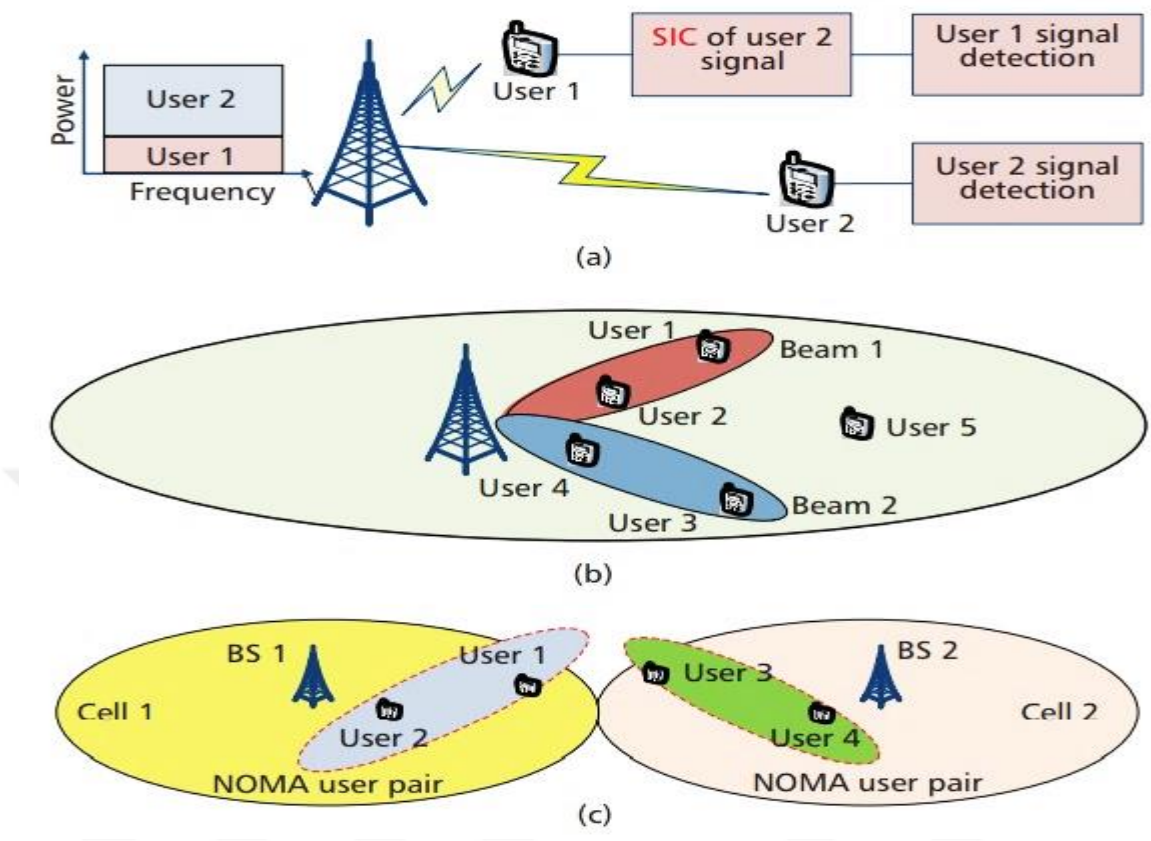

Figure 2. Three examples of PD-NOMA multiplexing illustration: (a) Simple NOMA using a SIC receiver, (b) NOMA in MIMO systems, and (c) NOMA network.

In order to balance the sum rate of all multiplexed users and the fairness of throughput among individual users, signals for various users are linearly added up at the BS transmitter under specific power partitioning. Multi-user detection (MUD) is often achieved at the receiver using SIC. The channel conditions may differ dramatically among users as a result of the near-far effect. It is recommended to do SIC in descending sequence of SINR for users with a high signal-to-interference-plus-noise ratio (SINR). As it can be seen, the fundamental NOMA with SIC utilizes the SINR differences between users, whether as a result of the near-far effect or of the transmitter's non-uniform power distribution. Uplink system capacity can be increased by employing a similar approach.

- NOMA in Massive MIMO Systems:

Multi-user with MIMO (MU-MIMO) and NOMA can be combined to increase the system's spectrum efficiency (Higuchi and Kishiyama, 2013).

Figure 2b shows how various transmit antennas at a base station (BS) are used to create various signals and beams in the spatial domain, each of which uses the fundamental NOMA outlined above (Ding, Lei, *et al.*, 2017). Spatial filtering at the receiver helps reduce inter-beam interference. (Higuchi and Kishiyama, 2013), and then the inter-user interference can be eliminated using intra-beam SIC. Massive MIMO systems' use of NOMA can increase spectral efficiency even more.

In the downlink NOMA scenario, where transmit power allocation favors users located farther away, cell edge users may encounter heightened interference from neighboring cells. Figure 2c illustrates a two-user NOMA setup within a cellular system comprising two cells and four users. BS 1 serves User 1 and User 2, while BS 2 caters to User 3 and User 4. It's noteworthy that Users 1 and 3 are expected to contend with significant interference, potentially impacting network or multicell performance. To alleviate inter-cell interference, one potential solution is the joint precoding of NOMA users' signals across adjacent cells. However, implementing this approach presents challenges, requiring access to all users' data and Channel State Information (CSI) at various Base Stations (BSs). Selecting the optimal precoder becomes a complex task. Additionally, the precoder used for geographically separated BS antennas may not generate a physical beam suitable for intra-beam NOMA, making the multi-user precoding utilized for single-cell NOMA impractical in the network NOMA scenario.

To tackle this issue, a complexity-reduced precoding scheme for network NOMA is proposed in (Han et al., 2014). This scheme applies a multi-cell joint precoder exclusively to cell edge users (e.g., User 1 and User 3, as depicted in Figure 2c). The rationale behind this approach lies in the significant differences expected in large-scale fading between links to different cells.

1.2.2 Code Domain NOMA Multiplexing

- Low-Density Spreading CDMA:

Low-Density Spreading Code Division Multiple Access (LDS-CDMA) is a modulation technique used in wireless communication systems to allow multiple users to transmit data simultaneously over the same frequency band. Unlike traditional CDMA systems where each user is assigned a unique spreading code with high spreading factor, (LDS-CDMA) employs spreading codes with lower spreading factors (Hoshyar, Wathan and Tafazolli, 2008).

In LDS-CDMA, spreading codes are designed to have a lower density, meaning that fewer chips in the spreading code sequence are nonzero compared to traditional CDMA systems. This results in a wider chip duration and less interference between users, allowing for improved performance in scenarios with a high number of users (Kschischang, Frey and Loeliger, 2001; P. Rashidi and A. Jamalipour, 2007).

LDS-CDMA offers several advantages over traditional CDMA systems. Firstly, it reduces interference between users by employing spreading codes with lower density. This reduction in interference leads to improved signal quality and higher capacity in the system. Additionally, LDS-CDMA demonstrates increased robustness due to its wider chip duration, which makes it less susceptible to issues like multipath fading and other channel impairments. Despite using lower spreading factors, LDS-CDMA maintains comparable spectral efficiency to traditional CDMA systems. This means that it can effectively utilize the available spectrum while achieving enhanced spectral efficiency, making it a promising technology for wireless communication systems. In order to lessen interference at each chip, LDS-CDMA substitutes sparse spreading sequences for the dense spreading sequences used in traditional CDMA. LDS-CDMA can therefore enhance system performance by utilizing LDS sequences in CDMA (Hoshyar, Wathan and Tafazolli, 2008), It is the primary difference between standard CDMA and LDS-CDMA. With the right spreading sequence design, interference between several users will be effectively reduced, and overloading can be accomplished. Multi-user detection (MUD) can be implemented at the receiver using a message passing algorithm (MPA). MPA performs incredibly well for the factor graph (Kschischang, Frey and Loeliger, 2001; Higuchi and Benjebbour, 2015), which, as shown in Figure 3, is a bipartite graph with variable and factor nodes.

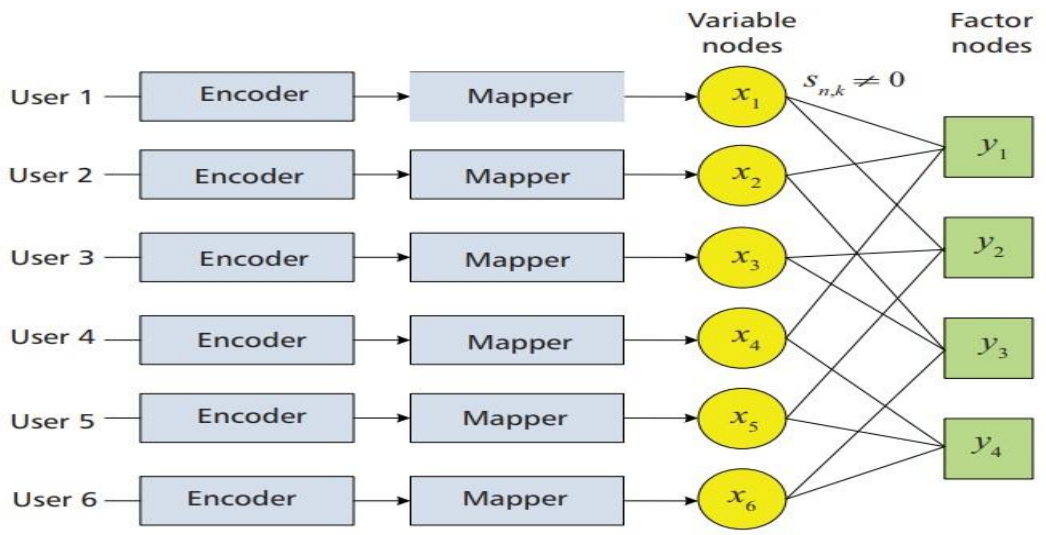

Figure 3. Six users with four transmission chips, or 150 percent overload, is an example of LDS-CDMA (Kschischang, Frey and Loeliger, 2001).

- Low-Density Spreading OFDM (LDS-OFDM):

Low-Density Spreading Orthogonal Frequency Division Multiplexing (LDS-OFDM) is a modulation technique that offers unique advantages in wireless communication systems. Unlike traditional OFDM systems, LDS-OFDM utilizes spreading codes with lower density, resulting in reduced interference between users. This reduction in interference enhances signal quality and increases system capacity. Additionally, LDS-OFDM exhibits increased robustness due to its wider chip duration, making it less susceptible to multipath fading and other channel impairments. Despite using lower spreading factors, LDS-OFDM maintains comparable spectral efficiency to traditional OFDM systems, allowing for efficient utilization of the available spectrum. Overall, LDS-OFDM holds promise for improving the performance and reliability of wireless communication networks.

LDS-OFDM uses chips that are subcarriers of OFDM to counteract multipath fading, it can implement a hybrid of LDS-CDMA and OFDM. The transmitted symbols in LDS-OFDM are first mapped to specific LDS sequences before being sent on various OFDM subcarriers. In order to increase spectral efficiency, overloading is permitted when the number of symbols exceeds the number of subcarriers (Al-Imari *et al.*, 2014). An LDS-OFDM receiver can make use of MPA in LDS-CDMA. LDS-OFDM, by substituting LDS for the dense spreading sequences of multi-

carrier CDMA (MC-CDMA), can be thought of as an enhanced version of this technology. Sparse Code Multiple Access (SCMA) with the most recent SCMA proposal (Nikopour and Baligh, 2013) is a developed form of LDS-CDMA. Figure 4 shows how SCMA, in contrast to LDS-CDMA, directly maps various bit streams to various sparse code words. There are six users in Figure 4, and each has a predefined codebook.

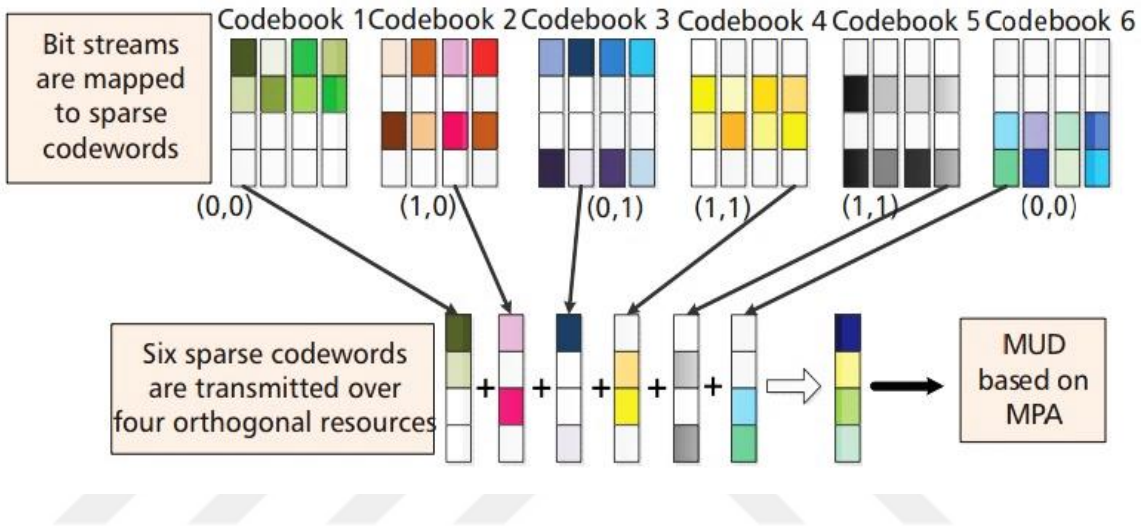

Figure 4: SCMA encoding and multiplexing.

In the realm of SCMA, strategic placement of zeros across different codebooks facilitates easier collision avoidance among users. Each code word within the same codebook shares zeros in specific dimensions, with two bits assigned to each intricate code word for individual users (Dai et al., 2015). The multiplexing of passwords for all users is achieved using four orthogonal shared resources, such as Orthogonal Frequency Division Multiplexing (OFDM) subcarriers.

The process of generating the N-dimensional constellation for each codebook involves several steps applied to the specific codebook. Initially, codebook-specific operations are applied to the mother constellation, resulting in an N-dimensional complex constellation with M points. These operations typically include phase rotation, complex conjugation, and dimensional permutation, aimed at optimizing shaping gain. Subsequently, each N-dimensional point undergoes multiplication by a projection matrix to produce a K-dimensional code word, where K is significantly larger than N (K >> N). This code word consists of N non-zero elements derived

from the components of the N-dimensional constellation point, ultimately yielding codebooks comprising M code words. Additional details are available in (Nikopour and Baligh, 2013).

- Multi-User Shared Access (MUSA):

Multi-User Shared Access (MUSA) is a communication technique that allows multiple users to share the same resources simultaneously. In MUSA, multiple users are allocated resources such as frequency bands, time slots, or code sequences to transmit their data. Unlike traditional communication systems where resources are exclusively assigned to individual users, MUSA enables efficient resource utilization by allowing multiple users to access the same resources concurrently. One of the key advantages of MUSA is its ability to improve spectral efficiency by accommodating multiple users within the same resource allocation. By sharing resources, MUSA can better utilize available bandwidth, time, or codes, thereby increasing the overall capacity of the communication system. Overall, Multi-User Shared Access (MUSA) offers a flexible and efficient approach to resource allocation in communication systems, making it suitable for various wireless communication applications ranging from cellular networks to satellite communications.

In the uplink MUSA system depicted in Figure 5, as illustrated by (Yuan, Yu, and Li, 2015), the symbols of each user undergo spreading using a designated spreading sequence.

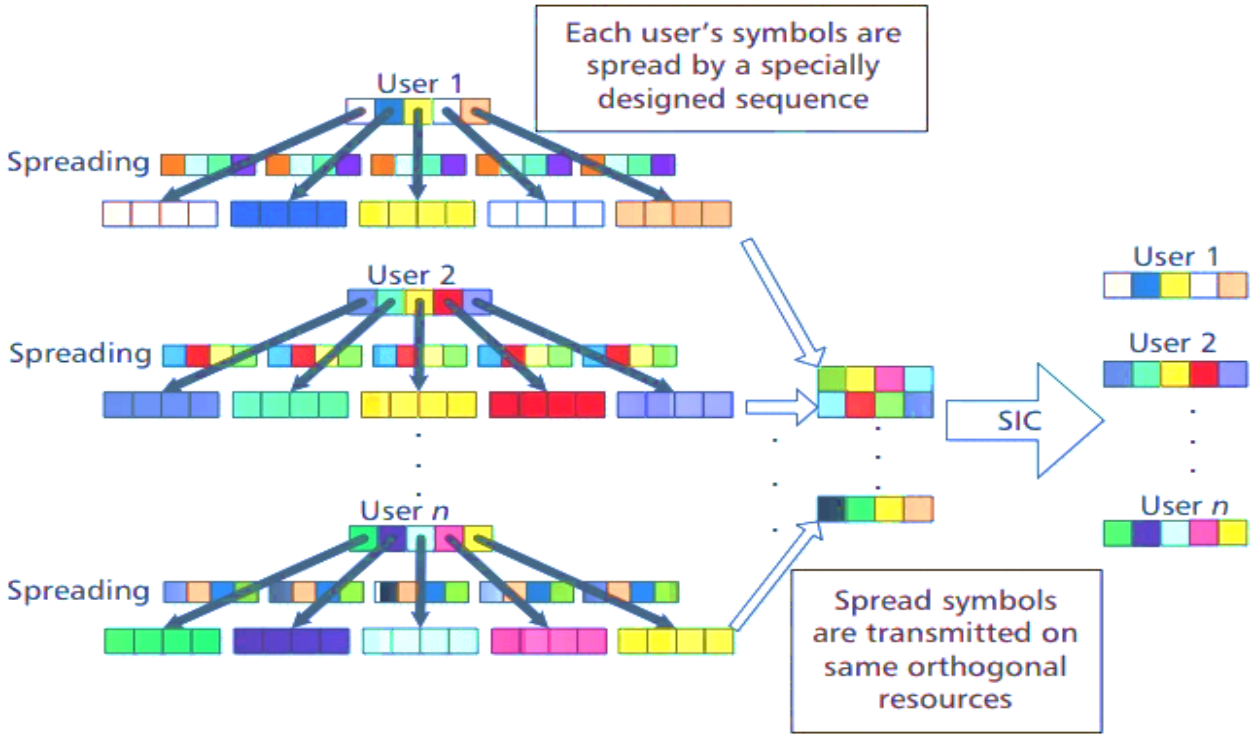

Figure 5: Uplink MUSA system.

In the uplink MUSA system, as depicted in Figure 6 by (Yuan, Yu, and Li, 2015), each user has the flexibility to randomly select one spreading sequence from a pool of many. A single user may employ multiple spreading sequences for different symbols, potentially enhancing performance through interference averaging. All spreading symbols are transmitted over the same time-frequency resources. The spreading sequences employed should exhibit low cross-correlation and may be M-ary.

At the receiver end, a code word-level SIC approach is utilized to differentiate between data from multiple users employing non-binary spreading sequences. Given that the receiver needs to decode data for all users regardless, the uplink complexity of code word-level SIC is less of a concern. The primary change to the receiver implementation involves adapting the processing pipeline to accommodate the SIC function. Unlike MC-CDMA, which doesn't necessitate synchronization in the uplink, MUSA operates under the assumption that user signals are essentially synchronous upon reaching the BS, simplifying the implementation of SIC.

1.2.3 Other NOMA Schemes

Furthermore to the previously discussed power and code domain multiplexing methods in NOMA, there are several other NOMA techniques. One such technique is NOMA Pattern-Division Multiple Access (PDMA), which can be implemented in various domains. PDMA employs non-orthogonal patterns at the transmitter, strategically maximizing diversity while minimizing overlaps among multiple users. This multiplexing technique operates within the spatial domain, the code domain, or a blend of both. Within the code domain, it aligns with the Successive Antenna Mapping Algorithm (SAMA), resembling LDS-CDMA but utilizing non-orthogonal patterns instead of LDS sequences.

Spatial PDMA, also referred to as spatial NOMA, necessitates multiple antennas at the Base Station (BS), enabling diverse transmit antennas to facilitate PDMA. Unlike multi-user MIMO, spatial PDMA does not require precoding, prioritizing spatial diversity over spectral efficiency. Both uplink and downlink transmissions can harness PDMA for efficient data transfer.

Bit-Division Multiplexing (BDM) stands out as another noteworthy NOMA variant, particularly advantageous for downlink transmission scenarios. Built upon hierarchical modulation principles, BDM partitions user resources at the bit level. Although multi-user signals share the same constellation, BDM's resource allocation technically maintains orthogonality in the bit domain.

Further adding to the NOMA repertoire is Interleave-Division Multiple Access (IDMA), a technique that interleaves chips post-spreading sequence multiplication of symbols. In densely populated systems facing a 200 percent overload and a bit error rate (BER) of 10e-3, IDMA demonstrates an impressive Eb/N0 gain of approximately 1 dB compared to CDMA, as evidenced by (Kusume, Bauch, and Utschick, 2011).

1.3 Problem Statement

- The evolution of data communication has resulted in new data transmission challenges, including reduced Bit Error Rates (BER), better data throughput, and the lowest latency.
- To achieve this, channel optimization becomes essential, aiming to transfer user data with minimal channel fading, such as the Additive Gaussian Noise (AWGN) model or

Rayleigh channel fading model. Among the techniques employed for optimizing channel specifications, the use of multiple access schemes stands out with the key challenges revolve around system throughput and fairness.

- For multi-users and in many applications such as large data and big video transmission where data amount is huge, NOMA system may not meet the required specifications of the 5G like low BER, high capacity and throughput. As a result and for multi-users NOMA system must yield efficient optimization algorithms like the machine and deep learning techniques rather than being mixed through conventional multiplexing techniques.

1.4 Objectives

This study aims to comprehensively investigate NOMA, covering its fundamental principles, distinguishing features, and evaluating its advantages and limitations. The primary focus is on analyzing spectral efficiency, overall system performance, and receiver complexity through extensive simulation experiments. To achieve this, MATLAB programs have been developed to simulate various NOMA communication scenarios, leveraging deep learning techniques to enhance and evaluate Bit Error Rate (BER) performance across all users. Furthermore, this research seeks to address challenges and explore opportunities in NOMA design, while also outlining future research directions in the field. The overarching objective is to optimize the NOMA system parameters with a certain DL model to minimize BER, with subsequent comparison against classical systems to demonstrate performance improvement. Specifically, the objectives are as follows:

• Implementation of a multi-user data transmission system utilizing uplink and downlink NOMA technology.

• Enhancement of system performance by optimizing power gain coefficients in uplink and downlink NOMA channels using a deep learning approach with DNN model.

• Evaluation of BER performance under varying power gain coefficients and Signal-to-Noise Ratio (SNR) conditions to monitor channel reliability.

1.5 Motivation

The rapid advancement of mobile communication technologies, evolving from 1G to 4G, has predominantly revolved around optimizing multiple access strategies. Traditionally, OMA techniques, which allocate resources across time, code, frequency, or time-frequency domains to efficiently manage communication channels. However, OMA's reliance on orthogonal resources imposes limitations on the system's scalability, necessitating careful synchronization and resource allocation to accommodate a growing number of users. To address the challenges outlined above and enhance the performance of communication networks, incorporating NOMA with deep learning techniques presents a promising solution. By leveraging deep learning algorithms, such as neural networks, we can optimize NOMA systems to achieve improved spectral efficiency, lower latency, and enhanced reliability. Here's how the integration of NOMA with deep learning can help overcome the identified challenges:

1. Enhanced Resource Allocation: Deep learning algorithms can analyze complex patterns and optimize resource allocation in NOMA systems more efficiently than traditional methods. By dynamically adjusting power allocation and user pairing based on real-time channel conditions and traffic demands, deep learning enables NOMA to achieve higher spectral efficiency and accommodate a larger number of users.
2. Adaptive Channel Estimation: Deep learning algorithms can learn from historical channel data to predict future channel conditions accurately. By continuously updating channel state information (CSI) and adapting transmission parameters accordingly, NOMA systems can mitigate the effects of fading channels and improve overall system performance.
3. Intelligent User Pairing: Deep learning algorithms can intelligently pair users with similar channel characteristics to maximize the benefits of NOMA transmission. By considering factors such as channel quality, user mobility, and data requirements, deep learning-enabled NOMA systems can optimize user pairing strategies to enhance system throughput and fairness.

1.6 Contributions of this Work

This study makes significant contributions to the field of cellular mobile communication by deploying Non-Orthogonal Multiple Access (NOMA) systems with recurrent neural networks (RNN). Unlike traditional estimation methods, deep learning (DL) eliminates the need for explicit channel estimation, offering unparalleled efficiency and adaptability. The integration of DL into NOMA systems represents a paradigm shift in wireless communication, overcoming the limitations of sequential processing and explicit channel estimation associated with conventional approaches like successive interference cancellation (SIC). By automatically learning and recognizing patterns in data, DL significantly enhances the efficiency and simplicity of receivers, enabling them to handle multiple users seamlessly while mitigating error propagation effects that can enhance the BER of the received signals.

Moreover, this study extends the capabilities of NOMA systems beyond theoretical frameworks by demonstrating practical implementation and performance evaluation. While the investigated work can accommodate N-users, the proposed deep neural network (DNN) approach achieves remarkable two-user detection in a single-step process, showcasing the efficiency and effectiveness of DL in real-world scenarios.

1.7 Thesis Organization

The thesis consists of five chapter:

1. Chapter one shed lights on Introduction which contains the problem statement, motivations and the objectives of the proposed work.
2. Chapter two provides the NOMA with Deep Learning theoretical background and Literature Review of the work.
3. Chapter three deals with the System Model, which contains the actual implanted system.
4. Chapter Four discusses the Simulation Results and Discussion.
5. Chapter Five contains the Conclusion and Future Works.

CHAPTER TWO

NOMA WITH DEEP LEARNING

2.1 Introduction

One of the significant tool for increasing the capacity of the system for desired cellular systems with suitable and rational expense is adapting radio access technology (RAT) design. Multiple access schemes such as TDMA, CDMA, FDMA, OFDMA, and OMA are perfect and efficient technologies of radio access. However, these methods give the ability to different users for accessing or sharing many radio resources in same time with several limitations.

In contrast, traditional NOMA employs a superposition coding technique at the transmitter and Successive Interference Cancellation (SIC) at the receiver. This approach surpasses orthogonal multiplexing in terms of information-theoretic performance and optimally utilizes the capacity region of the downlink broadcast channel.

To further enhance NOMA's capabilities, recent researches have explored integrating machine learning (ML) or deep learning (DL) techniques, leveraging their ability to adaptively learn and optimize system performance. This integration promises to revolutionize the efficiency and capacity of cellular systems, paving the way for more advanced and cost-effective RAT designs.

Basically, NOMA-DL combines NOMA and DL techniques as a powerful tool that enhances NOMA systems by addressing key aspects like power allocation and channel estimation. NOMA-DL can show great potential in improving wireless communication performance. NOMA-DL systems can decode messages without explicit channel estimation, surpassing traditional methods and reducing error propagation.

2.2 Deep Learning in Wireless Communication

The field of wireless communication is advancing rapidly, driven by the promise of technologies like 5G and the forthcoming 6G network. Within this landscape, deep learning (DL)

techniques have emerged as powerful tools offering significant benefits and advantages for wireless communication systems.

DL, a subset of machine learning, focuses on developing and applying neural networks is capable of autonomous learning and decision-making. These neural networks empower wireless communication systems to adapt and optimize various aspects of data transmission and reception, unlocking new levels of efficiency and performance. One of the key advantages of DL in wireless communication lies in its capacity to handle complex, non-linear relationships inherent in wireless channels. Neural networks excel at capturing intricate patterns in data, enabling more precise and efficient signal detection, modulation, and error correction. Figure 6 shows a NOMA model constructed using DL. The hidden layer is used for identification and retraining. Multiple neurons are especially present in hidden layers.

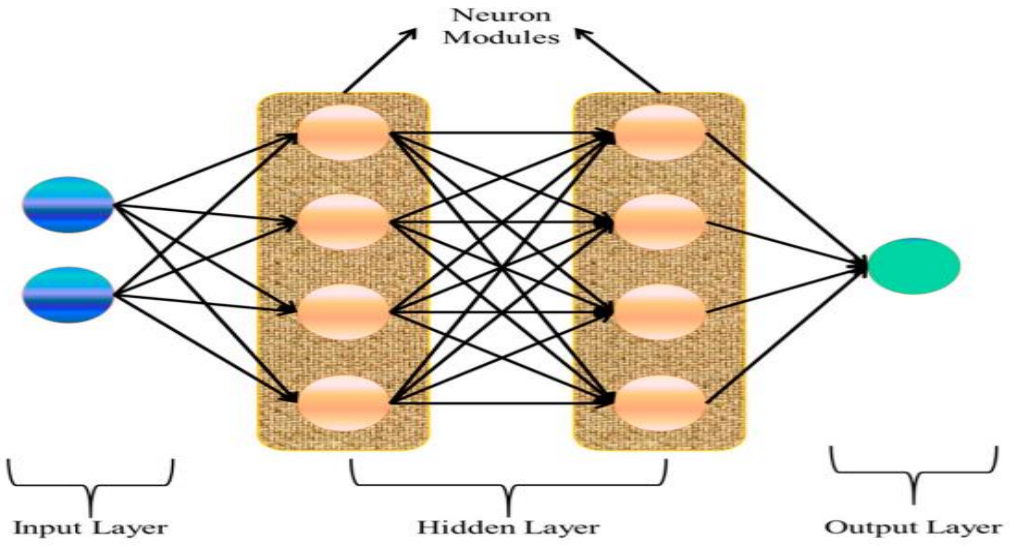

Figure 6. Basic deep neural network general framework (Mohsan, Syed Agha Hassnain, et al. 2023)

In the context of 5G and future 6G networks, DL can facilitate enhanced spatial multiplexing, allowing multiple data streams to be transmitted simultaneously using the same frequency resources. By leveraging DL algorithms, wireless systems can dynamically allocate these resources, considering factors such as the surrounding environment, user demands, and signal quality. DL techniques offer unparalleled opportunities for optimizing wireless communication

performance, enabling adaptive resource allocation and efficient error correction. Additionally, DL can contribute to reducing interference in wireless communication by analyzing interference patterns with neural networks, mitigating the impact of neighboring signals and improving overall signal quality and reliability.

To illustrate the potential of DL in wireless communication, imagine a scenario where a cell tower transmits data to multiple users simultaneously, each with different signal qualities and requirements providing users with more reliable, secure, and efficient connectivity. DL algorithms can dynamically adjust signal properties for each user, optimizing transmission and reception based on real-time feedback and network conditions. This integration has the potential to revolutionize various industries, including telecommunications, healthcare, transportation, and smart cities. As an example of NOMA-DL, one of the levels in Figure 7 is referred to as the background noise level, and it allows for the use of additive-white Gaussian noise to tamper with the processed signal. Using current channel models and thorough training of the input information, the CSI can be dynamically generated. The use of CSI of various settings gathered from models is intensively educated on arbitrary sequences of the input signals. Offline education is the term for this kind of instruction. In order to accurately forecast the channel's surroundings, the output signals can also be included in the training information. The CSI can be transmitted in real-time by pilot signals, and the input signals can be trained using that data. Online learning is the term for this sort of education.

Figure 7 shows a block architecture of the NOMA technology that incorporates both online and offline training for the auto-detection of CSI. The channel can be estimated using DL while taking bad weather into consideration. For identifying continuously varying channels, for instance, DL with long-short term memory (LSTM) is employed. Here, the hidden layers can serve as a kind of network state memories, allowing the DL especially to store, recall, and analyze the earlier intricate information.

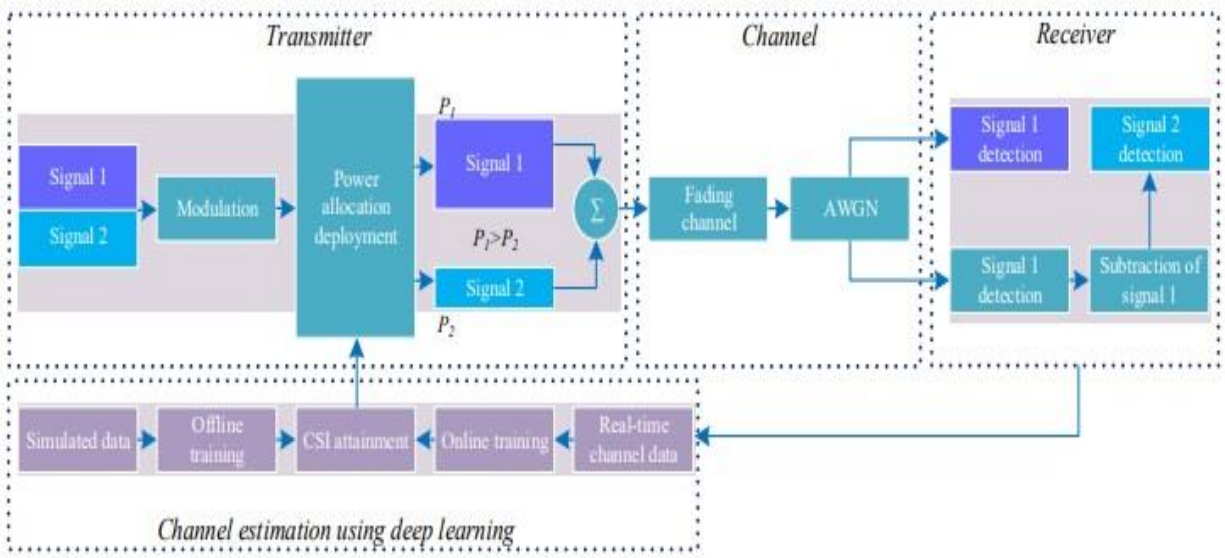

Figure 7. NOMA system block diagram using both online and offline DL methods.

By harnessing DL methodologies, NOMA systems can effectively address challenges such as complex computational processes, rapidly fluctuating channel conditions, and the necessity for precise CSI. Deep learning facilitates the automated analysis of CSI to enhance data encoding, decoding, and channel detection. In contrast to conventional techniques like Successive Interference Cancellation (SIC), deep learning-driven NOMA systems exhibit superior performance by adeptly managing channel distortions and overlapping signals from multiple users. Recent research indicates that deep learning significantly boosts detection capabilities in MIMO-NOMA systems when compared to traditional approaches. By leveraging neural networks to find optimal solutions, deep learning emerges as a potent tool for signal detection within NOMA systems. Furthermore, by integrating deep learning with cutting-edge technologies like MIMO, there is an optimized allocation of power that leads to improved data rates and energy efficiency. In essence, the integration of deep learning into wireless communication systems transforms NOMA technology by surmounting inherent limitations and elevating overall system performance (Mohsan, Syed Agha Hassnain, et al, 2023; Lin, C., et al, 2019).

2.3 NOMA-DL Schemes

The deep learning approach provides a more efficient alternative to traditional signal detection methods like SIC method. By utilizing DL models like recurrent neural networks (RNNs), convolutional neural networks (CNNs), and long-short term memory (LSTM), NOMA-DL configurations can achieve increased throughput, reduced latency, and enhanced resource management. The incorporation of DL in wireless communication has created pathways for augmenting data transmission speeds and network effectiveness within 5G environments.

2.3.1 Recurrent Neural Networks (RNN) in NOMA

RNN is a type of neural network that employed in processing sequential data, making it well-suited for modeling wireless communication channels. By capturing temporal dependencies and context in the received signals, RNNs can effectively mitigate interference and improve the overall system performance. When integrated into NOMA systems, RNNs can enhance the decoding process by intelligently extracting and utilizing contextual information from the received signals. This enables more accurate demodulation and decoding, leading to improved signal reconstruction and higher data rates. Furthermore, RNNs can adapt dynamically to varying channel conditions, allowing them to optimize resource allocation in real-time. This adaptive characteristic is particularly beneficial in wireless communication scenarios where channel conditions fluctuate rapidly. The use of RNNs in NOMA can also enable the detection of multiple users simultaneously, further enhancing the capacity and efficiency of the system. By leveraging the sequential learning capabilities of RNNs, NOMA schemes can achieve greater spectral efficiency, making them ideal for future wireless communication networks.

RNNs offer a promising approach for enhancing the performance of NOMA systems. By leveraging their ability to capture temporal dependencies and adapt to changing channel conditions, RNN-based NOMA schemes can effectively mitigate interference and improve the overall wireless communication quality. Table 1 shows the comparison of RNN-based NOMA with traditional NOMA schemes.

Table 1. Comparison of RNN-based NOMA with traditional NOMA schemes

NOMA Scheme	Advantages	Limitations
RNN-based NOMA	• Improved decoding accuracy • Dynamic adaptation to channel conditions • Simultaneous detection of multiple users	• Complex implementation • Higher computational requirements • Training and optimization challenges
Traditional NOMA	• Lower complexity • Less computational overhead • Established implementation techniques	• Potential interference and error propagation • Less efficient in dynamic channel conditions

2.3.2 Convolutional Neural Networks (CNN) in NOMA

Convolutional Neural Networks (CNN) have emerged as a powerful deep learning (DL) technique with applications in various fields, including wireless communication. In the context of NOMA systems, CNN can be employed to optimize wireless communication performance.

CNN is particularly well-suited for tasks such as image and signal processing, making it a valuable tool for NOMA schemes. By leveraging the inherent hierarchical structure of CNNs, wireless communication systems can benefit from enhanced feature extraction and improved decision-making capabilities. One of the key advantages of CNN in NOMA is its ability to handle complex wireless communication scenarios by automatically learning relevant patterns and relationships from the input data. This allows CNN to effectively extract meaningful features from received signals, leading to improved decoding accuracy and overall system performance.

Furthermore, CNN-based NOMA models have been shown to possess superior resilience to noise and interference, enabling reliable communication in challenging environments. The use of CNN can also mitigate issues related to channel estimation and interference cancellation, improving the overall spectral efficiency of NOMA systems.

To demonstrate the benefits of CNN in NOMA, the following table 2 showcases a comparison between traditional NOMA techniques and CNN-based NOMA approaches:

Table 2. Comparison of CNN-based NOMA with traditional NOMA schemes

NOMA Techniques	CNN-based NOMA Approaches
• Dependent on manually creating specific features	• Automatic feature extraction
• Vulnerable to interference and noise	• Improved resilience to interference and noise
• Limited decoding accuracy	• Enhanced decoding accuracy
• Lower overall spectral efficiency	• Improved spectral efficiency

2.3.3 Long Short-Term Memory (LSTM) in NOMA

Long Short-Term Memory (LSTM) model is a type of recurrent neural network (RNN) that has shown remarkable success in various applications, including natural language processing and time series analysis.

In the context of NOMA, LSTM models offer significant advantages by effectively modeling the temporal dependencies and long-term dependencies present in wireless communication systems. By capturing the dynamics and patterns in the transmission data, LSTM can enhance the reliability and efficiency of NOMA schemes.

LSTM networks consist of memory cells that can store information over extended periods of time, allowing them to remember and learn from past inputs. This long-term memory capability enables LSTM models to make accurate predictions based on historical data, making them well-suited for addressing the challenges and complexities of wireless communication. These memory cells, coupled with input, output, and forget gates, enable LSTM models to control the flow of information and selectively retain or discard relevant information at each time step. This ability to process sequential data and retain important context makes LSTM a powerful tool for improving the performance of NOMA systems. By integrating LSTM models into NOMA techniques, wireless communication systems can benefit from enhanced error correction, improved resource allocation, and better interference mitigation. LSTM's ability to learn and adapt to changing wireless channel conditions can lead to increased capacity and higher spectral efficiency. Overall, by incorporating LSTM models into NOMA schemes as explained in table 3, wireless communication systems can achieve superior performance in terms of reliability, efficiency, and spectral utilization.

Table 3. Advantages of LSTM-based NOMA schemes

LSTM in NOMA	**Advantages**
• Effective modeling of temporal dependencies	• Improved accuracy in predictions
• Enhanced error correction	• Higher reliability of transmissions
• Adaptability to changing channel conditions	• Real-time optimization of resource allocation
• Interference cancellation and suppression	• Better signal quality in NOMA

2.4 Benefits of using NOMA-DL in wireless networks

By integrating NOMA and DL techniques, wireless communication systems can achieve enhanced throughput, decreased bit-error-rate (BER), reduced latency, efficient task scheduling, optimized resource allocation, and improved user pairing. The fusion of DL-driven NOMA with state-of-the-art technologies like Intelligent Reflecting Surfaces (IRS), Mobile Edge Computing (MEC), Simultaneous Wireless Information and Power Transfer (SWIPT), Orthogonal Frequency Division Multiplexing (OFDM), and Multiple-Input Multiple-Output (MIMO) further amplifies the efficiency and capacity of wireless networks.

Recent studies have highlighted how DL-enabled NOMA systems address traditional NOMA complexities such as high computational demands, intricate designs, and resource allocation challenges. Leveraging DL methodologies for tasks like channel estimation, power management, user equity, and transceiver optimization enables NOMA systems to achieve heightened energy efficiency and superior performance overall. Moreover, integrating DL-based NOMA into 5G networks facilitates faster data transfer rates, improved network utilization, expanded system capacity, reduced latency, and enhanced management of power consumption.

The incorporation of NOMA with DL presents a promising pathway for future wireless technologies by surmounting the constraints of conventional NOMA systems. With ongoing research endeavors concentrating on optimizing the performance of DL-based NOMA systems and tackling technical obstacles, the adoption of this integrated approach is poised to catalyze innovations in wireless communication networks for years to come (Amin, S, et al, 2023).

2.5 Applications of NOMA-DL in 5G networks

2.5.1 Enhancing data transfer speeds with NOMA-DL

NOMA enables the efficient multiplexing of multiple users into the transmission power domain, thereby enhancing spectral efficiency. By grouping users based on channel gain disparities, NOMA organizes them non-orthogonally on the same spectrum resources. On the other hand, DL provides sophisticated signal processing methods that can significantly enhance signal detection and resource allocation in wireless communication systems.

To enhance data transfer speeds with NOMA-DL, it is crucial to optimize power allocations within NOMA clusters using DL models like RNN, CNN, and LSTM. These models can effectively learn distinct patterns associated with each user cluster, resulting in more precise signal detection and improved system performance. Moreover, DL can aid in adaptive coding and modulation in downlink NOMA systems, further amplifying data transfer speeds.

In practical settings such as IoT networks or 5G deployments, NOMA-DL has displayed promising outcomes in augmenting throughput and energy efficiency. By merging the advantages of NOMA's spectral efficiency with DL's intelligent signal processing capabilities, wireless networks can experience significant improvements in data transfer speeds. Real-world applications and case studies have proven the efficacy of NOMA-DL in achieving high throughput rates and optimizing resource utilization.

Overall, the collaboration between NOMA and DL holds immense potential for transforming wireless communication systems by elevating data transfer speeds, enhancing network efficiency, and enabling seamless connectivity in upcoming technologies (Emir, A., et. al., 2021; Shipon Ali, M., et. al., 2016; Kumar, A., et. al., 2024; Supraja, G., et. al. 2023).

2.5.2 Improving network efficiency and capacity in 5G

By combining the power domain of NOMA alongside DL algorithms, signal detection and resource allocation can be finely tuned for optimal performance. Utilizing a user cluster strategy with DL models such as neural networks facilitates the effective management of diverse user groups, leading to enhanced signal detection and resource utilization. Furthermore, the integration of NOMA and DL allows for signal distribution based on channel state information, maximizing throughput and spectral efficiency. Research indicates that cooperative NOMA systems, involving nearby users as relays or utilizing UAVs for relay transmission, can further bolster overall performance and reliability in disaster management scenarios. Moreover, the amalgamation of NOMA with decode-and-forward relaying protocols using UAVs has the potential to enhance communication efficiency for IoT devices in disaster-stricken areas. In essence, the convergence of NOMA and DL techniques offers a significant opportunity to meet

the escalating demands for efficient wireless communication in 5G networks (Kumar, R., et. Al, 2023; Sim, I., et. al, 2020; Basnayake, V., et. al., 2020).

2.5.3 Real-world applications in the industry

An example of the merging of NOMA and DL methodologies to enhance performance within mobile edge computing (MEC) setups. Through the utilization of NOMA-IRS technology, there is a possibility to achieve enhanced communication coverage and energy efficiency, addressing the requirements for high spectral efficiency and minimal latency in 5G networks. Additionally, DL models such as RNN, CNN, and LSTM play a vital role in accelerating data transmission rates and network effectiveness by enabling predictive beamforming algorithms to optimize average sum rates. Furthermore, employing DL algorithms for signal detection in massive-MIMO-NOMA systems showcases advancements in spectral efficiency, user satisfaction, and overall system functionality. These practical scenarios underscore the importance of amalgamating NOMA with deep learning to transform wireless technologies for future breakthroughs (Amin, S., et. al, 2023; Kumar, A., et. al., 2024).

2.6 NOMA-DL Literature Review

A great deal of study on 5G communications has been prompted by the new and growing needs for highly reliable as well as ultrahigh bandwidth wireless communication. Systems for communication gain a great deal from the rapid advancements in deep learning (DL) and NOMA technology. This review offers a comprehensive look into DL-based NOMA for the expansion of 5G networks. It examines numerous studies on NOMA, DL, and their uses in 5G communication (Senapati and Tanna, 2022). The intricacy of conventional administration of resources techniques poses a formidable obstacle to the effectiveness of computing. In order to address this issue, (Yang et al., 2019) proposed a resource management strategy leveraging a deep neural network

(DNN). This approach offers the advantage of nearly real-time resource allocation, as the DNN executes a simple operation. It addresses the resource management challenges in NOMA systems employing imperfect Successive Interference Cancellation (SIC) technology at the receivers, encompassing both power allocation and user scheduling stages. The designed fully-connected DNN approximates the energy allocation achieved by the interior point method (IPM) during the energy allocation phase. This not only enhances computational efficiency but also boosts the overall system sum rate. Additionally, the user scheduling algorithm is executed based on the allocated power to further increase the framework's sum rate. Simulation results confirm the effectiveness of the proposed algorithms.

One theory holds that machine learning (ML) will be the engine of the next revolution in technology due to its superior nonlinear simulation capabilities, it can resolve the correlation issue at the receiver. DNNs are more useful in a larger range of circumstances due to their faster processing speed and lower cost. In the past few years and recently, many studies have used DNNs for handling different kinds of communication. For example, (Mao *et al.*, 2017), (Farsad and Goldsmith, 2018) a number of tasks, including decoding, anomaly detection, signal recovery, and resource management, have shown promise when using DNN (Yang *et al.*, 2019). According to (Hasan *et al.*, 2020), DL is used in multiple places in NOMA. For analyzing complicated information and obtaining ideal CSI, DL can be quite helpful. Online and offline training are two different types of training that can be distinguished in NOMA.

Despite specific programming, ML may offer answers to complicated issues, and the findings can be executed with high precision (Morocho-Cayamcela, Lee and Lim, 2019). The use of ML algorithms can significantly improve wireless communication effectiveness (Sejan *et al.*, 2022). ML algorithms are given data samples, and upon studying the information, the model can make an estimate (Sejan, Rahman and Song, 2022). Numerous studies have been done to use the ML approach to address the problems related to channel state information (CSI), channel estimation, and signal detection. For a DL-NOMA system, a deep neural network (DNN) with a bi-directional long short-term memory (Bi-LSTM) based multiuser joint channel estimation and signal detection is presented.

In (Rahman et al., 2022), Convolutional neuronal networks (CNN) along with the suggested model are compared with regard to Symbol Error Rate (SER) in order to assess the effectiveness

of the latter. Additionally, the accuracy of the Bi-LSTM's SER is assessed in considerations of various SNRs employing a Monte Carlo simulation. Results indicate that the suggested model's performance is comparable to traditional NOMA-SIC approaches, including the CNN model, Least Squares (LS), and Minimum Mean Square Error (MMSE).

2.7 Fifth Generation (5G) Technology

With the advent of fifth-generation (5G) technology and architect as shown in Figure 8, users can experience unprecedentedly high bandwidth, marking a significant bound in wireless communication capabilities. Unlike its predecessors, 5G offers a excess of cutting-edge features and functionalities that cater to diverse user needs. Alongside established technologies like third-generation mobile networks (Talukdar and Saikia, 2014), Wi-Fi, WiMAX, LTE, and sensor networks such as Bluetooth and ZigBee, 5G introduces novel advancements such as LASCDMA (Large Area Synchronized Code Division Multiple Access), OFDM, MC-CDMA, UWB (Ultra-wideband), Network-LMDS (Local Multipoint Distribution Service), and IPv6 (Das, 2017).

The promise and marks of 5G lie in its ability to support a wide range of services and applications, from enhanced data capabilities to unlimited call volumes and seamless data transmission. By leveraging the latest mobile operating systems, 5G paves the way for unparalleled connectivity and unprecedented user experiences. Anticipated to roll out by 2020 (GWO and Learning, 2021), 5G networks are poised to revolutionize global connectivity with their sophisticated architecture and limitless potential.

At the core of 5G network architecture is the All-IP Network (AIPN), serving as a unified platform for all radio access technologies (RATs). This architecture enables seamless integration of various services and applications, including mobile portals, commerce, healthcare, banking, and more, through Cloud Computing Resources (CCR). Cloud computing facilitates on-demand access to configurable computing resources, allowing users to access data and applications remotely without the need for local installations (Dixit, 2015).

The Reconfigurable Multi Technology Core (RMTC) plays a pivotal role in managing the diverse array of radio access technologies supported by 5G, including 2G/GERAN, 3G/UTRAN, 4G/EUTRAN, and others like IS/95, EV-DO, and CDMA2000. Through interoperability processes and criteria, RMTC ensures seamless communication between endpoints and various access mechanisms, thereby providing users with flexibility and choice in their connectivity

options. Overall, 5G technology promises to deliver unprecedented levels of connectivity, efficiency, and versatility, ushering in a new era of wireless communication that transcends the limitations of previous generations (Utpal Jyoti Bora, 2013).

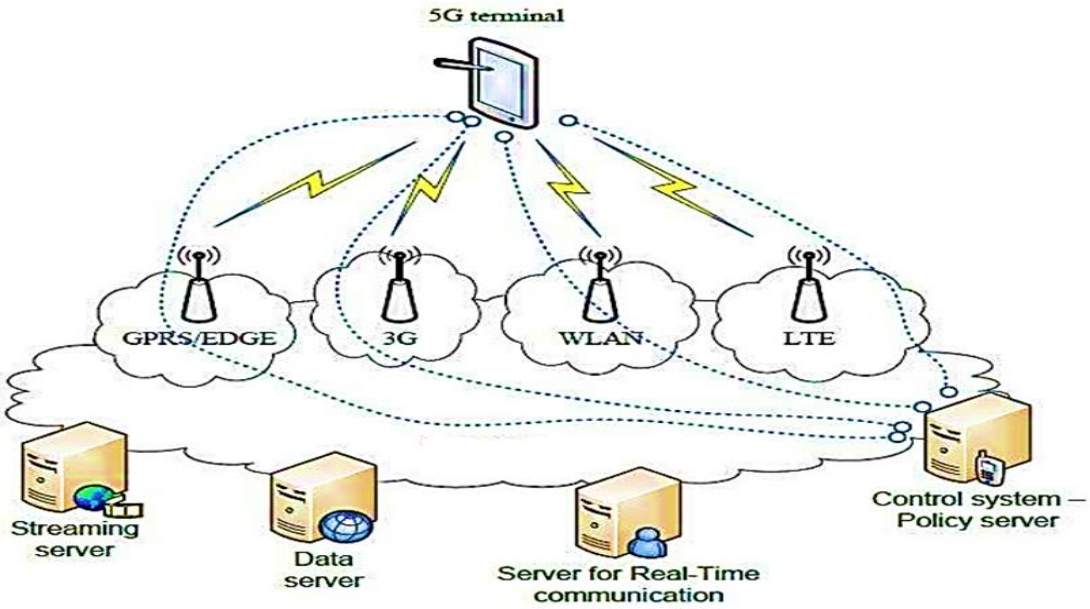

Figure 8. 5G Architecture (GWO and Learning, 2021)

Furthermore, the quality of service (QoS) in 5G communication systems stands out as unparalleled. QoS encompasses a network's ability to regulate and deliver diverse aspects of network performance, encompassing metrics such as latency, error rate, and uptime. It entails the management of network resources by assigning priority to different types of data, such as video, audio, and documents, over the internet. This prioritization is especially crucial for applications like video on demand, Internet Protocol Television (IPTV), Voice over Internet Protocol (VoIP), streaming media, video conferencing, and online gaming.

The key objectives of QoS implementation revolve around allocating dedicated bandwidth to critical applications, mitigating jitter, minimizing latency, and enhancing loss characteristics. QoS technologies serve as foundational components for upcoming commercial applications across campus networks, wide-area networks, and internet service provider networks. In essence, QoS plays an indispensable role in optimizing network performance by effectively managing

resources, prioritizing critical applications, and reducing latency for time-sensitive data. These capabilities are paramount for ensuring a dependable and responsive network, particularly in environments characterized by diverse traffic types and varying performance demands.

2.8 Features of Fifth Generation Technique

5G technology can provide, employ, and enhance the following issues:

• 5G technology boasts exceptionally high-speed transmission, enormous capacity, and cost-effectiveness, revolutionizing phone, video, internet, and broadband services while offering precise, bidirectional traffic data. It ensures global accessibility and service portability.

• With its high fault tolerance, 5G technology delivers top-notch services, ensuring high-quality experiences for users.

• Leveraging gigabit-speed transmission, 5G allows for approximately 65,000 simultaneous connections, facilitating the development of AI applications that seamlessly integrate with mobile devices and enhance various aspects of daily life.

• Through remote management capabilities, 5G technology provides users with faster and superior solutions, enhancing overall user experience.

• With incredibly high download and upload rates, 5G technology offers unparalleled bandwidth and resolution, catering to the needs of even the most demanding mobile phone users.

• 5G enables carrier-class gateways with unmatched reliability, ensuring seamless connectivity and consistent performance.

• The evolution of wireless and mobile phone networks is driven by all-IP techniques and improved transmission rates. Handheld devices continuously improve in processing power, onboard memory, and battery life, with 5G incorporating modern technologies such as cognitive radio, software-defined radio (SDR), nanotechnology, cloud computing, and an all-IP platform, paving the way for the next generation of mobile networks.

CHAPTER THREE

SYSTEM MODEL

3.1 Introduction

The proposed work is structured with two distinct parts, with the initial section focusing on simulating classical NOMA under different scenarios of transmitted power with different user distances and power allocations. This division aims to clarify the significant influence that varying levels of transmitted power. This empirical analysis of power-related variables forms an essential foundation for comprehending the broader implications and optimizing the NOMA scheme for enhanced performance under diverse conditions.

The second aspect of this research aims to conceptualize and develop a specialized DNN based on the recurrent type to perform the critical tasks of channel estimation and NOMA demodulation. It involves the intricate process of training the neural network, equipping with the capability to accurately decipher and delineate channel characteristics while concurrently performing efficient NOMA signal demodulation. The ensuing stage of analysis involves a comprehensive comparative evaluation, wherein the neural network's operation is meticulously juxtaposed against conventional estimators such as Least Square (LS) (Atitallah, et al, 2017), Maximum Likelihood (ML) (Yeom, et al, 2019), and Minimum Mean Square Error (MMSE) (Kumar, 2011) methodologies. Through this comparative framework, the study aims to elucidate the extent to which the neural network outperforms or aligns with conventional methods, thereby establishing its viability as a potent alternative or augmentation to existing approaches within the realm of NOMA communication systems.

3.2 Ordinary NOMA

3.2.1 NOMA Capacity

NOMA emerges as a promising multiple access technology for 5G, offering enhanced transmission capacity. It achieves this by enabling multiple users to transmit data simultaneously on the same frequency carrier. Superposition coding, employed at the transmitter, combines users'

signals in the power domain. Successive Interference Cancellation (SIC) at the receiver plays a crucial role in eliminating interference and separating individual user messages.

In a specific NOMA downlink scenario involving two users communicating with a BS, User 1 is positioned far away (weaker signal), and User 2 is nearby (stronger signal), with distances d_1 and d_2 from the BS, separately. The BS sends diverse and separate messages, x_1 to User 1 and x_2 to User 2. Assigning power allocation aspects $\alpha 1$ and $\alpha 2$, satisfying $\alpha 1 + \alpha 2 = 1$, determine the transmission power distribution. In NOMA, fairness is promoted by allocating more power to the far user ($\alpha 1 > \alpha 2$). That is, $\alpha 1 > \alpha 2$, Let h_1 and h_2 mean the channel from the BS to the far and the near user respectively as $|h_1|^2 < |h_2|^2$. The superposition coded NOMA signal communicated by the BS is:

$$x = x_{NOMA} = \sqrt{P}(\sqrt{\alpha_1}x_1 + \sqrt{\alpha_2}x_2) \tag{3.1}$$

Where, P is the transmit power. The x is received totally at the far user after propagating through channel $h1$ with:

$$y_1 = h_1.x + w_1 \tag{3.2}$$

Similarly, the x that is received at the near user after propagating through channel $h2$ is:

$$y_2 = h_2.x + w_2 \tag{3.3}$$

In more general for involving multiple users, where the power assign factors must be ordered as $a_1 > a_2 > \cdots a_N$, the NOMA signal x_{NOMA} is represented as:

$$x_{NOMA} = \sqrt{P}\sum_{i=1}^{N}(\sqrt{\alpha_i}x_i) \tag{3.4}$$

The received data $\mathcal{Y}_{i,NOMA}$ for user i is expressed as,

$$\mathcal{Y}_{i,NOMA} = x_{NOMA}h_i + w_i \tag{3.5}$$

Where w_i is the AWGN with nil average or zero mean (μ=0) and certain σ^2variance value. Replacing for x_{NOMA} from (3.1), we obtain,

$$\mathcal{Y}_{i,NOMA} = \sqrt{P}(\sqrt{\alpha_1}x_1 + \sqrt{\alpha_2}x_2 + \cdots \sqrt{\alpha_N}x_N)\, h_i + w_i \tag{3.6}$$

Examining this equation for User 1 (the farthest user) reveals practical implications:

$$\mathcal{Y}_{1,NOMA} = \sqrt{P}\left(\underbrace{\sqrt{\alpha_1}x_1}_{desired\ and\ dominating} + \underbrace{\sqrt{\alpha_2}x_2 + \cdots + \sqrt{\alpha_N}x_N}_{interfernce}\right)h_1 + w_1 \tag{3.7}$$

As User 1 has been allocated the highest power, their transmission dominates the received signal. User 1 directly decodes their own message, treating other users' communications as interference. The Signal-to-Interference-plus-Noise Ratio (SINR) for User 1's signal decoding is given by:

$$\gamma_{1,NOMA} = \frac{\alpha_1 P|h_1|^2}{\alpha_2 P|h_2|^2+\alpha_3 P|h_3|^2+\cdots+\alpha_N P|h_N|^2+\sigma^2} \tag{3.8}$$

For User 2, the received signal is:

$$\mathcal{Y}_{2,NOMA} = \sqrt{P}\left(\underbrace{\sqrt{\alpha_1}x_1}_{desired\ but\ dominating} + \underbrace{\sqrt{\alpha_2}x_2}_{desired} + \underbrace{\ldots\sqrt{\alpha_N}x_N}_{interfernce}\right)h_2 + w_2 \tag{3.9}$$

In this scenario, User 2 employs SIC to extract User 1's message from the received signal before decoding its own message. By removing User 1's message, User 2's message becomes the dominant part of the received signal, allowing for accurate decoding and retrieval of the intended information:

$$\mathcal{Y}_{2,NOMA} = \sqrt{P}\left(\underbrace{\sqrt{\alpha_2}x_2}_{desired\ and\ dominating} + \underbrace{\ldots\sqrt{\alpha_N}x_N}_{interfernce}\right)h_2 + w_2 \tag{3.10}$$

The SINR for User 2 to decode its own message can be expressed as follows:

$$\gamma_{2,NOMA} = \frac{\alpha_2 P|h_2|^2}{\alpha_3 P|h_3|^2+\cdots+\alpha_N P|h_N|^2+\sigma^2} \tag{3.11}$$

This SINR expression can be generalized for user i

$$\gamma_{i,NOMA} = \frac{\alpha_i P|h_i|^2}{\alpha_{i+1} P|h_{i+1}|^2+\cdots+\alpha_N P|h_N|^2+\sigma^2} \tag{3.12}$$

Incorporating equation (12) into the BER formula, it can express the overall BER for NOMA as:

$$BER_{NOMA} = \frac{1}{2}erfc\left(\sqrt{\frac{\gamma_{i,NOMA}}{2}}\right) \tag{3.13}$$

3.2.2 NOMA Outage Probability

In a network where two users, denoted as U_f (far user) and U_n (near user), are transmitting data to the base station (BS), their respective distances from the BS are represented by d_f and d_n. The Rayleigh fading coefficients for the far and near users are denoted by h_f and h_n respectively; where $d_f > d_n$ and $|h_f|^2 < |h_n|^2$.

$$y = \underbrace{\sqrt{P}x_f h_f}_{\text{far user term}} + \underbrace{\sqrt{P}x_n h_n}_{\text{near user term}} + w \quad (3.14)$$

For uplink NOMA to function effectively, it is crucial that there be significant differences in user channel gains. If the channel gains are similar, the BS may struggle to distinguish between them in the power spectrum. In such cases, power management becomes essential, necessitating the use of varying power levels in their transmissions.

One important observation from the earlier discussion is the reversal of the SIC order in uplink NOMA. Unlike in downlink NOMA, where decoding starts with the signal from the remote user, in uplink NOMA, decoding commences with the signal from the closest user (Tabassum et al., 2017; Y. Liu et al., 2018). In this scenario, the signal from the near user is decoded first, treating the signal from the distant user as interference. The achievable rate for decoding near-user data at the BS can be expressed as:

$$R_n = \log_2\left(1 + \frac{P|h_n|^2}{P|h_f|^2 + \sigma^2}\right) \quad (3.15)$$

The maximum achievable throughput for the distant user following successive interference cancellation (SIC) can be computed as:

$$R_f = \log_2\left(1 + \frac{P|h_f|^2}{\sigma^2}\right) \quad (3.16)$$

3.2.3 BER of NOMA-Multiple users with QPSK

We are presently utilizing a single frequency carrier with QPSK modulation for all users in the network. Let's consider three NOMA users labeled U_1, U_2 and U_3. Their respective distances from the BS are denoted as d_1, d_2 and d_3 with $d_1 > d_2 > d_3$. U_1 is the farthest and weakest user, while U_3 is the nearest and strongest user to the BS. Corresponding Rayleigh fading coefficients are represented by h_1, h_2, and h_3 ordered such that, $|h_1|^2 < |h_2|^2 < |h_3|^2$. (The channels are behaved due to $h_i \propto \frac{1}{d_i}$). Power allocation coefficients, denoted as α_1, α_2 and α_3, follow the NOMA principle of prioritizing the user with the lowest transmission power and priority, leading to the ranking $a_1 > a_2 > a_3$. While fixed power allocation is used here for

simplicity, dynamic power allocation algorithms could enhance performance further. Let x_1, x_2 and x_3 represents the QPSK modulation messages that the BS intends to transmit to U_1, U_2 and U_3 correspondingly (Saito, et al., 2017). Then, the super-position coded signal sent by the BS is expressed as:

$$x = \sqrt{p}(\sqrt{a_1}x_1 + \sqrt{a_2}x_2 + \sqrt{a_3}x_3) \tag{3.17}$$

The received signal $\mathcal{Y}$ at the ith user is obtained by,

$$\mathcal{Y}_i = h_i x + n_i \tag{3.18}$$

Where the noise n_i is the specified normal distributed AWGN at receiver U_i. The SIC interpreting process is as illustrated in figure 9.

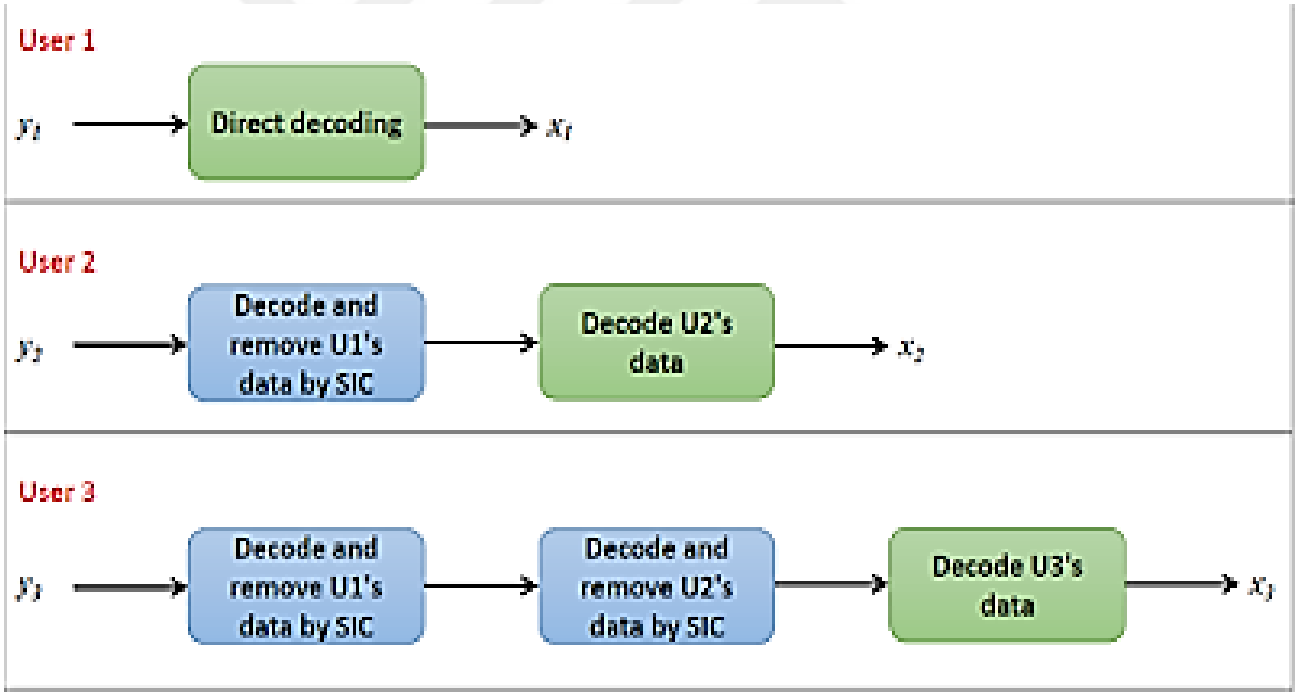

Figure 9. The SIC decoding process (Kara, et al., 2018).

At User 1

Since U_1 is assigned the highest power allocation, it can directly decode its message from the received signal Y_1. In this decoding process, the signals intended for U_2 and U_3 are treated as

interference. The achievable rate for U_1, which represents the rate at which U_1 can reliably receive its intended data, is expressed by this decoding process. The achievable rate U_1 is expressed as:

$$R_1 = log_2\left(1 + \frac{\alpha_1 P|h_1|^2}{\alpha_2 P|h_1|^2 + \alpha_3 P|h_1|^2 + \sigma^2}\right) \quad (3.19)$$

This can be further simplified as:

$$R_1 = log_2\left(1 + \frac{\alpha_1 P|h_1|^2}{(\alpha_2 + \alpha_3)P|h_1|^2 + \sigma^2}\right) \quad (3.20)$$

An important observation from the equation is that for U_1's signal to dominate both in the transmission (x) and the received signal ($\mathcal{Y}_1$), it's necessary that α_1 is greater than the sum of α_2 and α_3.

At User 2

The rate equation for U_2 is derived by applying SIC to eliminate U_1's data and treating U_3's signal as interference:

$$R_2 = log_2\left(1 + \frac{\alpha_2 P|h_2|^2}{\alpha_3 P|h_2|^2 + \sigma^2}\right) \quad (3.21)$$

To achieve successful interference cancellation, it's imperative that $\alpha_2 > \alpha_3$ plays a crucial role in the interference denominator part of the equation.

At User 3

For U_3 ($\alpha_3 < \alpha_1$, $\alpha_3 < \alpha_2$), SIC is executed twice to eliminate U_1 and U_2 information from y3. The dominance of the α_1 term in y3 necessitates its elimination before any other terms. The achievable rate for U_3 is:

$$R_3 = log_2\left(1 + \frac{\alpha_3 P|h_3|^2}{\sigma^2}\right) \quad (3.22)$$

3.2.4 NOMA Simulation

A MATLAB script is written to simulate NOMA system and show the system outputs under the transmitted power change effect. The simulated system specified with 10^5 Montecarlo simulation, maximum SNR of 30 dB, variable power weight for each user. AWGN channel is used in the simulation. The BER for each user is plotted with respect to SNR for each transmitted case.

This pseudo-code represents the key operations and flow of the MATLAB script, using generic function calls for operations like modulation, superposition coding, AWGN channel simulation, direct decoding, interference cancellation, and BER calculation. You can adapt these function calls based on your programming environment. Here's the pseudo-code for the provided MATLAB script:

1. Set the number of Monte Carlo simulations to N = 10^5.

```
N = 10^5      // Number of Montecarlo simulations
```

2. Define the range of Signal-to-Noise Ratios (SNR) from 0 to 30 dB.

```
SNR = [0, 1, ..., 30]  // SNR range in dB
```

3. Convert the SNR values from dB to linear scale using db2pow.

```
snr = db2pow(SNR)      // Convert SNR to linear scale
```

4. Generate random data bits for transmission for both User 1 and User 2.

```
// Generate random data bits for transmission

x1 = randomBits(N)    // Data bits of user 1

x2 = randomBits(N)    // Data bits of user 2
```

5. Modulate the generated data bits using Binary Phase Shift Keying (BPSK) modulation.

```
// BPSK modulation of data

xmod1 = bpskModulation(x1)

xmod2 = bpskModulation(x2)
```

6. Input power allocation values for User 1 and User 2 ensuring that the sum of their allocations equals 1.

```
// Set power weights for users

a1 = input user1 allocation power value 1

a2 = input user2 allocation power value 2

a1+a2=1
```

7. Perform superposition coding simulation by combining the modulated signals of both users based on their power allocations.

```
// Superposition coding simulation

for i = 1 to length(a1):

x = superpositionCoding(xmod1, xmod2, sqrt(a1[i]), sqrt(a2))
```

8. For each power weight and SNR value:

a. Corrupt the combined signal with Additive White Gaussian Noise (AWGN).

b. Simulate the reception at each user.

c. Attempt direct decoding of the received signal to recover the transmitted data for both users.

d. Perform interference cancellation to recover the data for User 2 after decoding User 1's signal.

e. Calculate the Bit Error Rate (BER) for each user.

```
 for u = 1 to length(snr):

    y1 = awgnChannel(x, snr[u])  // Received signal at user 1 corrupted by AWGN

    y2 = awgnChannel(x, snr[u])  // Received signal at user 2 corrupted by AWGN

    // User 1

    x1_hat = directDecoding(y1)  // Direct decoding of x from y1

    // User 2

    x11_est = directDecoding(y2)  // Direct decoding of x from y2
```

```
rem = y2 - sqrt(a1[i]) * x11_est  // Subtract remodulated x11_est from y2

x2_hat = interferenceCancellation(rem)  // Decode x2 from remaining signal
```

9. Plot the BER curves against SNR for analysis.

```
// BER calculation

ber1[u] = calculateBER(x1, x1_hat)

ber2[u] = calculateBER(x2, x2_hat)

// Plot BER curves

plotBER(SNR, ber1, ber2, a1[i])
```

3.3 NOMA with deep neural networks

Exploring the depths of the NOMA system for data extraction from Channel State Information (CSI), the dataset is partitioned into training and testing components. The investigation centers on the DL on the NOMA receiver that can detect the signals generated from the uplink NOMA system, leveraging recurrent neural networks (RNN). The methodology involves handling data sequences, where each sequential moment is treated as a unique subcarrier. Notably, while multiple users can concurrently access the same subchannel, this study confines the scenario to two users. BER during this process is characterized as the mean rate at which these bit errors happen throughout the communication procedure:

$$\text{BER} = \frac{\text{Number of error bits}}{\text{Total number of transmitted bits}} \tag{3.23}$$

3.3.1 DL architecture

The DL architecture in this study as shown in Figure 10 and table 4 which are comprise several dilated conventional layers.

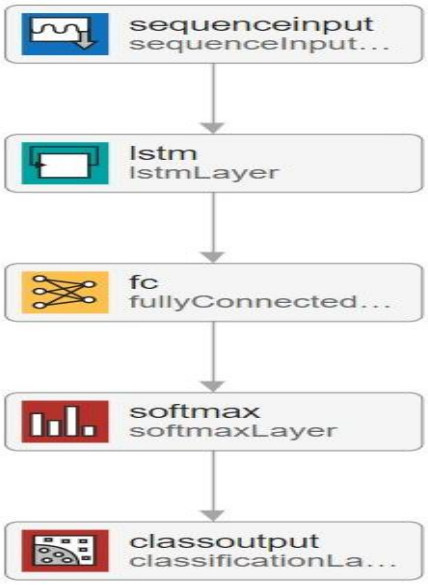

Figure 10. RNN/DL model layers

Table 4. RNN/DL structural layers

ANALYSIS RESULT

	Name	Type	Activations	Learnable Prope...	States
1	sequenceinput Sequence input with 384 dimensions	Sequence Input	384(C) x 1(B) x 1(T)	-	-
2	lstm LSTM with 128 hidden units	LSTM	128(C) x 1(B)	InputWeigh... 512 x... RecurrentW... 512 x... Bias 512 x...	HiddenSta... 128 x... CellState 128 x...
3	fc 16 fully connected layer	Fully Connected	16(C) x 1(B)	Weights 16 x 128 Bias 16 x 1	-
4	softmax softmax	Softmax	16(C) x 1(B)	-	-
5	classoutput crossentropyex with '1' and 15 other cla...	Classification Output	16(C) x 1(B)	-	-

3.3.1.1 Long Short Term Memory (LSTM) layers

It is capable of managing long-term dependencies and performing time series predictions using an approximate gradient algorithm. Additionally, it updates the weight matrices after each time step (Salama, W. M., et. al., 2023). The standard LSTM network comprises four gates, illustrated in Figure 11. Each individual gate can be modified as follows:

$$h_t = LSTM(h_{t-1}, X_t, P) \tag{3.24}$$

Where LSTM(.) denoted the processing propagations, X_t is the input state, and P presented the parameters of all LSTM network refers.

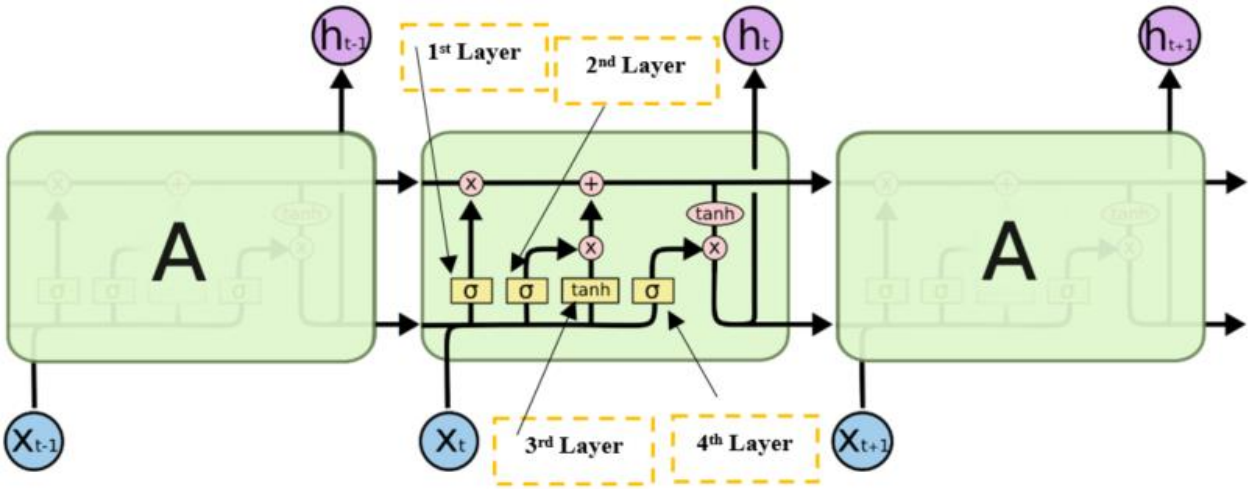

Figure 11. LSTM module contains four interacting layers

LSTM employs both the sigmoid (σ) and hyperbolic tangent (tanh) activation functions for its gates (Tweneboah-Koduah, S., et. al., 2022). It's crucial to note that the sigmoid function compresses it between (0 and 1), while the tanh function normalizes its input within the range of (-1 to 1).

3.3.1.2 Fully Connected layer

Fully Connected (FC) layers refer to flattened layers that interconnect with each other, signifying a network where multiple input layers are connected to various hidden layers and eventually fully connected to the output layers during the feed-forward process of neural networks (Basnayake, V., et. Al., 2020). In the realm of Fully Connected Neural Networks (FCNNs), the architecture is

characterized by a design where all nodes or neurons in one layer establish connections with the neurons in the subsequent layer (Mohsan, S. A. H., et. Al., 2023).

3.3.1.3 Softmax layer

The output layer in a neural network is presented through the activation function known as Softmax. This function serves the purpose of estimating the distribution of multinomial probabilities (Ogundokun, R. O., et. al., 2023). Softmax acts as a vital tool in the realm of multi-class categorization challenges, particularly when the need arises for more than two class indications.

3.3.1.4 Classification output layer

Within this category, the discrete process is expected to manifest in the variables of the output values. The input values (x) are subjected to the regression algorithm, wherein they are mapped to the output variable (y). The model's objective extends beyond regression and includes the task of classification, involving the mapping of input values to distinct variables (Budhiraja, I., et. al., 2024). The proposed model is structured as a 5×1 layer array, with the layers detailed in Table 5:

Table 5. The proposed model layers and dimensions

Name	**Type**	**Dimension**
sequenceinput	Sequence	Input Sequence input with 384 dimensions
Lstm	LSTM hidden units	LSTM with 128 hidden units
Fc	Fully Connected	16 fully connected layer
Softmax	Softmax	4PSK (QPSK)
classoutput	Classification Output	Cross entropy with 1 and 15 other classes

3.3.2 DL training model

In order to generate training data intended for signal detection within a two-user NOMA system. The key assumptions can be summarized as follows:

I. Each data packet is the relation between frequency with time and it composed of three distinct blocks: two pilot blocks and one data block. By employing QPSK modulation, the overall count of symbol combinations for two users (thus representing the quantity of unique labels) is calculated as 2^4=16. The generating training data samples are of size=320000, where each patch size on the input at each epoch=384.

II. To facilitate the neural network's acquisition of the relationship between the transmitted and received signals, the same pilot sequence is consistently utilized throughout the entirety of the simulation where the number of subcarriers=64.

III. The neural network undergoes training in a stable channel environment, characterized by specific parameters for the number of pilot subcarriers (NUM_{SC}) and the length of the cyclic prefix ($LENGTH_{CP}$). In order to assess the neural network's resilience, a random phase shift is introduced to each packet during testing.

3.3.3 NOMA/DL Simulation

In this part a MTLAB script is written to simulate the NOMA system with DNN. The purpose of this script is to generate training data intended for signal detection within a two-user NOMA system.

The neural network specified as: SeriesNetwork with properties:

Layers: [5×1 nnet.cnn.layer.Layer]

InputNames: {'sequenceinput'}

OutputNames: {'classoutput'}

The neural network specifications are:

layers =

5×1 Layer array with layers:

1 " Sequence Input Sequence input with 384 dimensions

2 " LSTM LSTM with 128 hidden units

3 " Fully Connected 16 fully connected layer

4 " Softmax softmax

5 " Classification Output cross entropy

The provided information describes a neural network configured as a SeriesNetwork with specific layers and properties. Here is a summarized breakdown of the neural network specifications:

1. Sequence Input Layer (layers(1)):

- Type: Sequence Input Layer
- Input Size: 384
- Min Length: 1
- Split Complex Inputs: No
- Normalization: None
- Normalization Dimension: Auto

2. LSTM Layer (layers(2)):

- Type: LSTM Layer
- Input Size: Auto
- Number of Hidden Units: 128
- Output Mode: Last
- State Activation Function: Tanh
- Gate Activation Function: Sigmoid
- Input Weights Initialization: Glorot
- Recurrent Weights Initialization: Orthogonal
- Bias Initialization: Unit-forget-gate

3. Fully Connected Layer (layers(3)):

- Type: Fully Connected Layer
- Input Size: Auto
- Output Size: 16
- Weights Initialization: Glorot
- Bias Initialization: Zeros

4. Softmax Layer (layers(4)):

- Type: Softmax Layer

5. Classification Output Layer (layers(5)):

- Type: Classification Output Layer
- Loss Function: Cross entropy
- Classes: Auto
- Class Weights: None
- Output Size: Auto

CHAPTER FOUR

SIMULATION RESULTS AND ANALYSIS

4.1. Ordinary NOMA

The simulation covers the effects of user power weight for two users NOMA communication system. For each power weight the BER is calculated and plotted with respect to the SNR. The outage probability of the two users at the transmitting to BS at uplink, and BER of the two users at the receiving from BS at downlink are representing the amount of errors in each bit of data once the analog signal is dispatched through the noisy channel. Outage prob. vs transmitted power of the near user BS is always is the better while BER vs SNR of the far user who has larger power allocation is always better. If the power gain allocations are of large span, the outage prob. will be comparable, while BER will be of large differ. Figures (12-17) show the outage prob. and BER for three different power allocation cases. The cases are:

case_1, the user1 is the far user with α_1=Pfar = 0.85 at distance 1000m and the user 2 with α_2=Pnear = 0.15 at distance 500m.

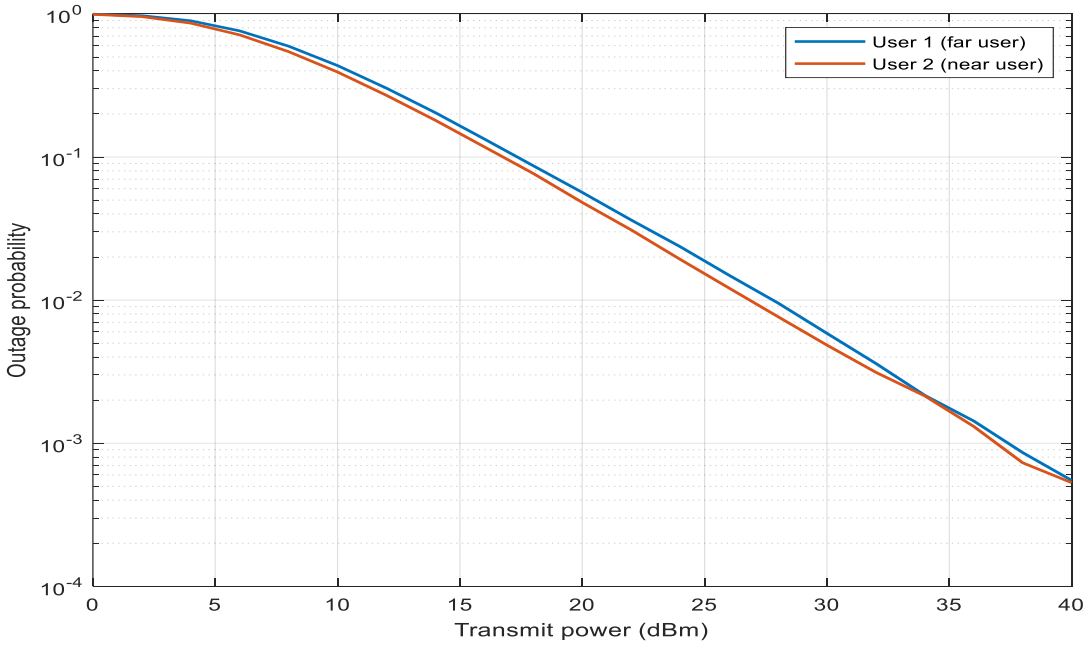

Figure 12. Outage prob. vs. transmitted power when $\alpha 1$ = 0.85 and $\alpha 2$ = 0.15

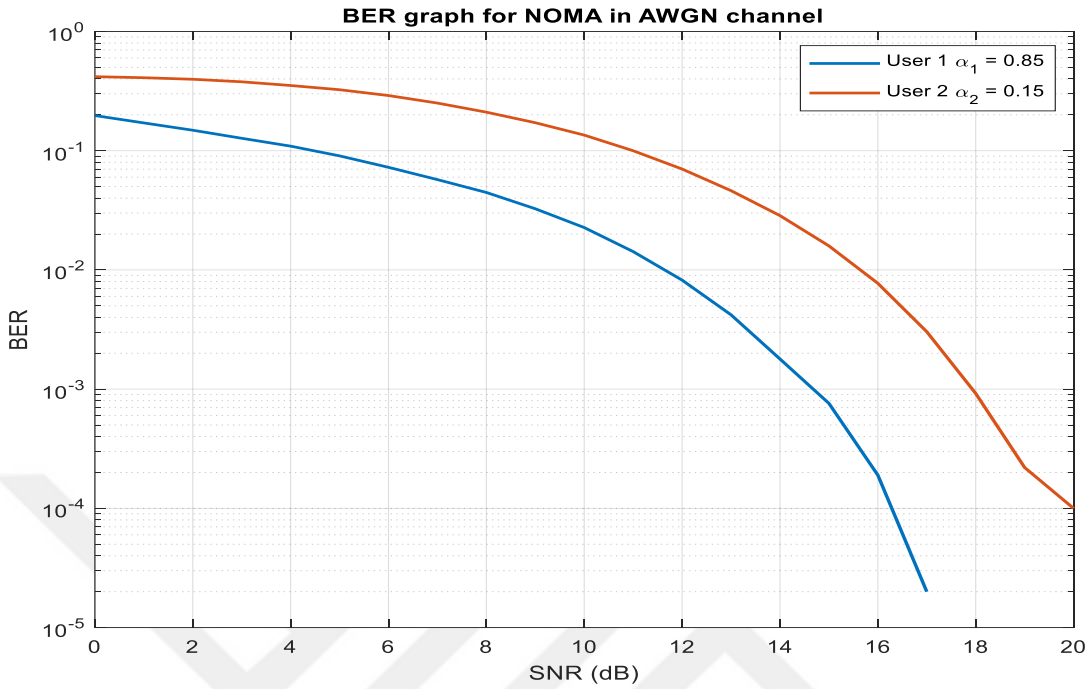

Figure 13. BER. vs. SNR when $\boldsymbol{\alpha}1 = 0.85$ and $\boldsymbol{\alpha}2 = 0.15$

case_2, the user1 is the far user with Pfar = 0.7 at distance1000m and the user 2 Pnear = 0.3 at distance 500m.

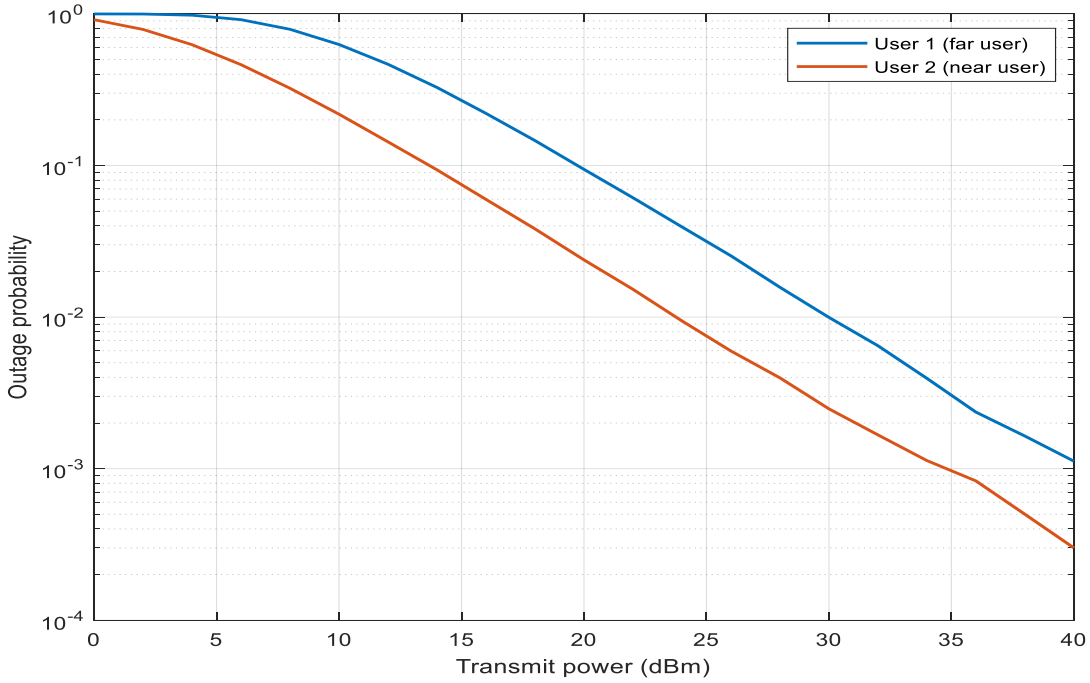

Figure 14. Outage prob. vs. transmitted power when $\boldsymbol{\alpha}1 = 0.7$ and $\boldsymbol{\alpha}2 = 0.3$

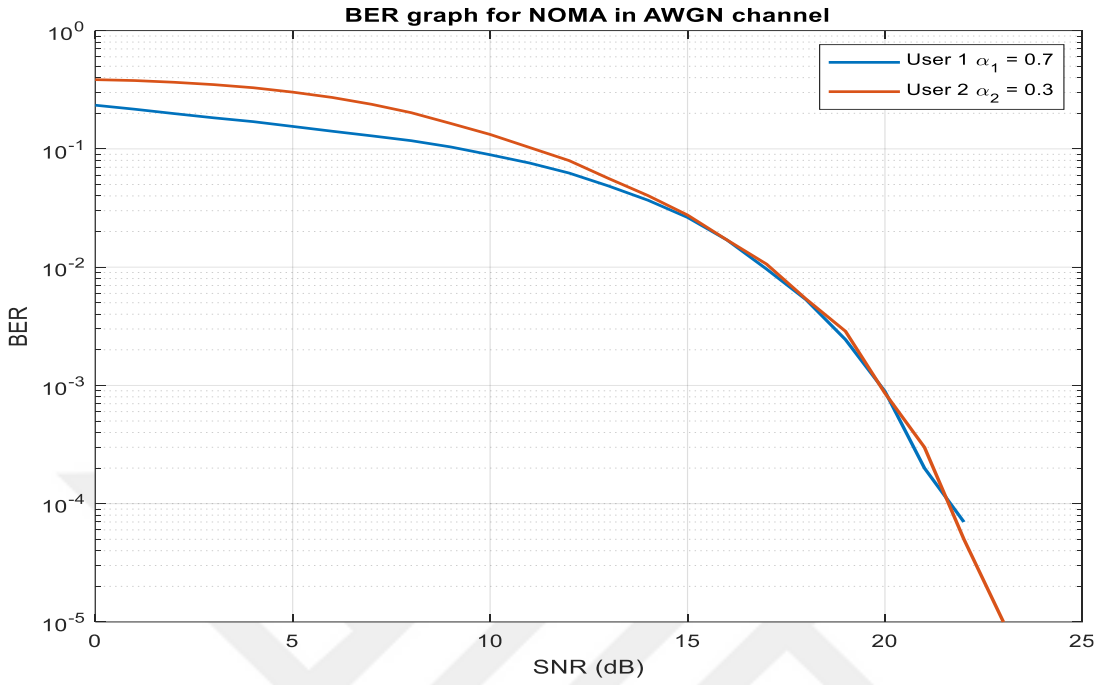

Figure 15. BER. vs. SNR when $\boldsymbol{\alpha}1 = 0.7$ and $\boldsymbol{\alpha}2 = 0.3$

case_3, the user1 is the far user with Pfar = 0.55 at distance 1000m and the user 2 Pnear = 0.45 at distance 500m.

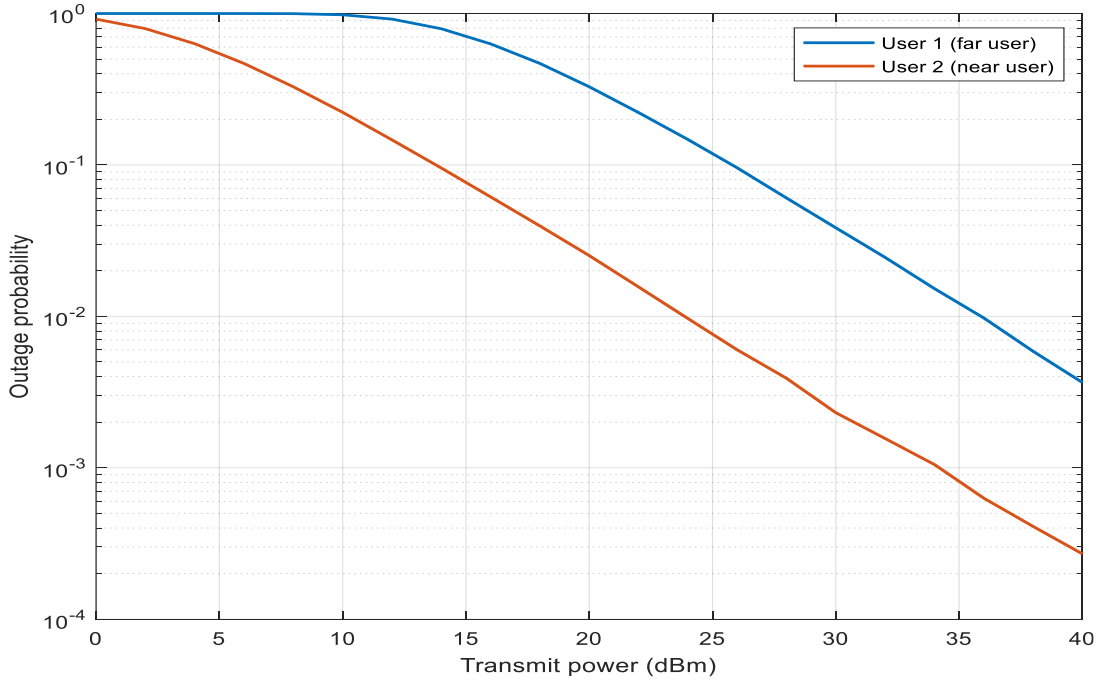

Figure 16. Outage prob. vs. transmitted power when $\boldsymbol{\alpha}1 = 0.55$ and $\boldsymbol{\alpha}2 = 0.45$

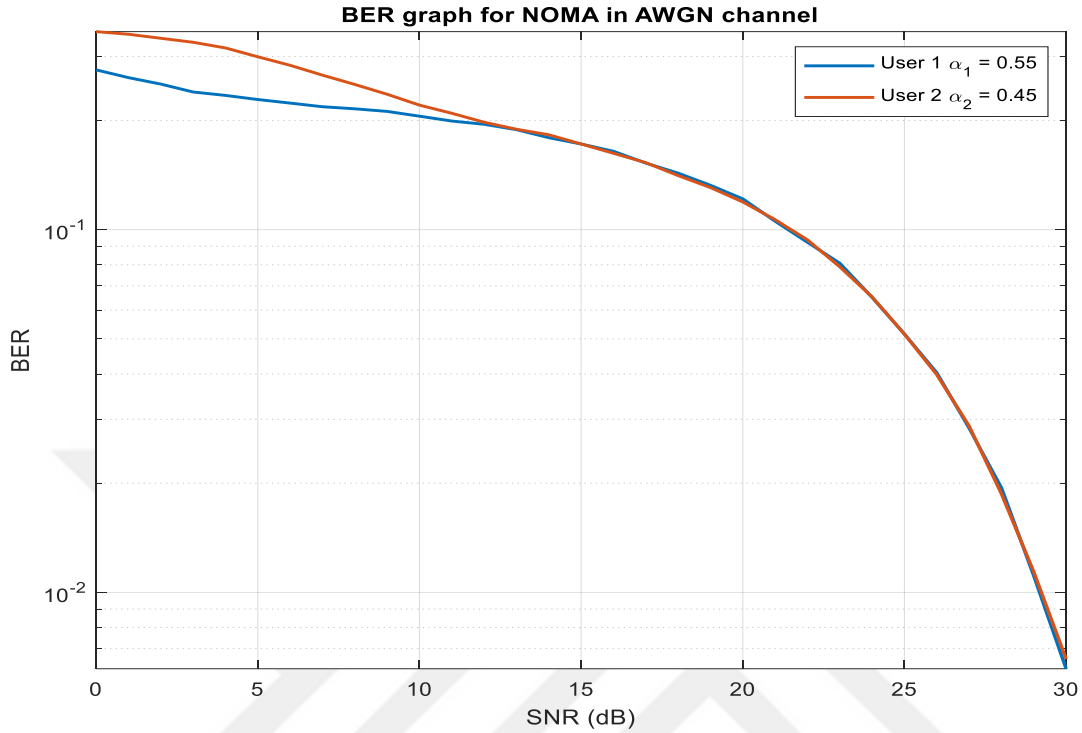

Figure 17. BER. vs. SNR when $\boldsymbol{\alpha}1 = 0.55$ and $\boldsymbol{\alpha}2 = 0.45$

4.2. DL/NOMA communication system

In this part, the proposed NOMA system with deep learning is simulated and executed within 50 epochs, each with 1000 iterations and with learning rate=1e-3. The training process is shown in figure 18.

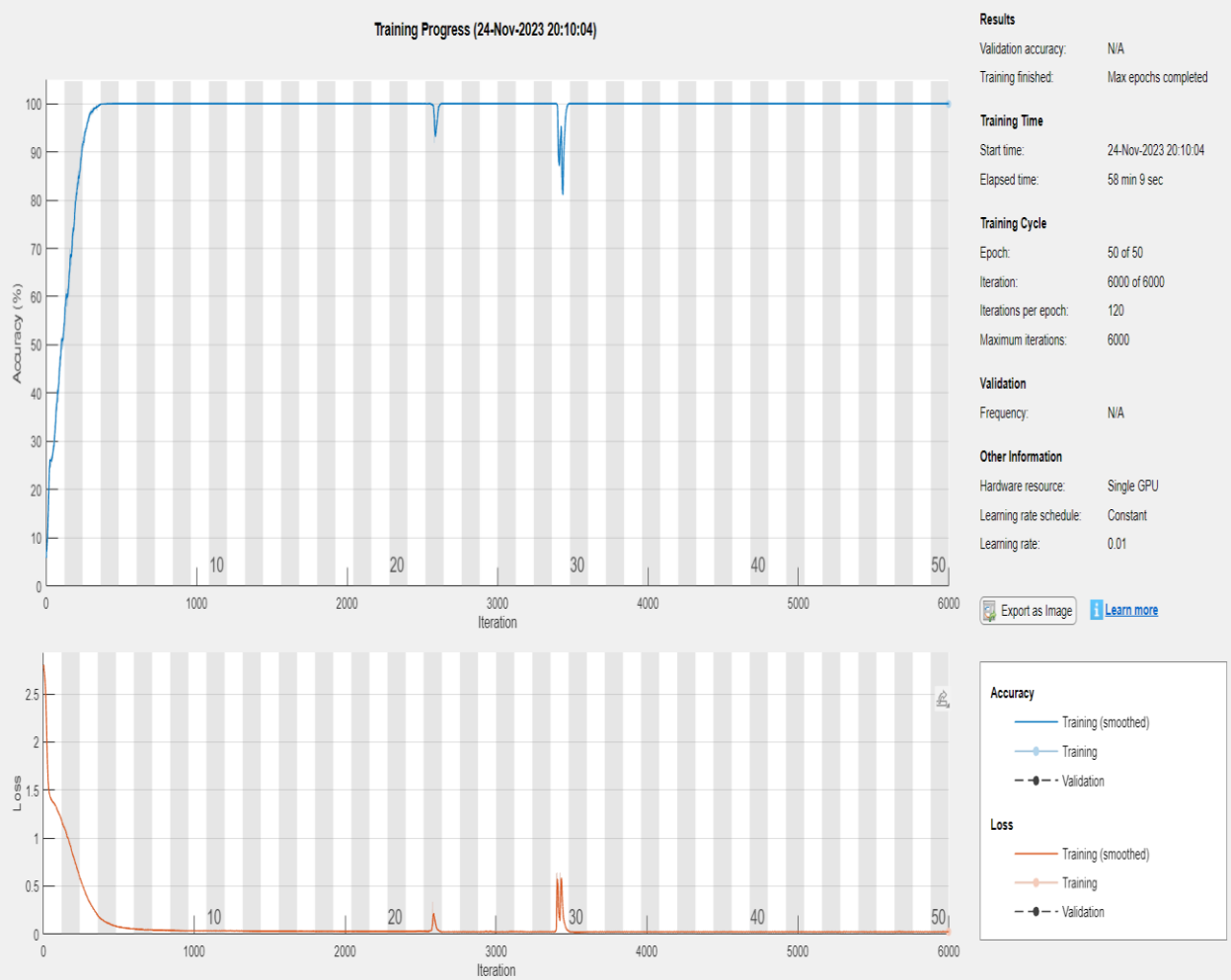

Figure 18. DL training process

Depending on the deep neural network discussed in chapter 3, a two users DL/NOMA system is simulated and implemented.

The simulation results for the deep learning NOMA system BER compared with BER for (LS, ML, and MLSE) techniques to show the performance of neural networks in NOMA applications. The simulation is done for two scenarios depending on the number of pilot subcarrier as:

Scenario_1:

No. of subcarrier pilots= NUM_{SC} =64, cyclic prefix length= $LENGTH_{CP}$ =16,

No. of feature vector=Batch size=64 subcarriers×3 blocks ×2 users=384.

Scenario_2:

NUM_{SC} =16, $LENGTH_{CP}$ =10,

No. of feature vector=Batch size=16 subcarriers×3 blocks ×2 users=96.

Figure 19 shows the BER for the far user only without NOMA, with classical NOMA, and with DL-NOMA. It is clear that the best BER is obtained from utilizing the DL.

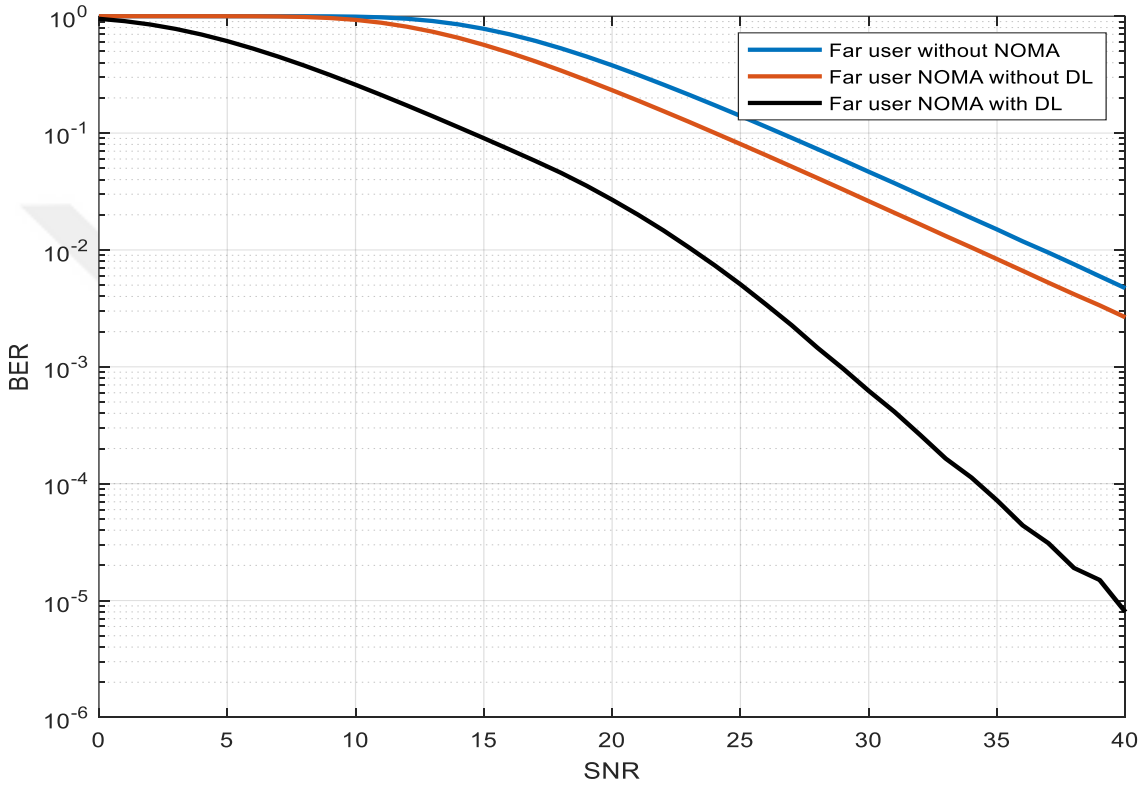

Figure 19. BER comparison for the far user

Figure 20 shows the BER for DL and least square error in case of 64 pilot subcarriers for the two users. The BER for both users in case of DL network system is better than that for LS method.

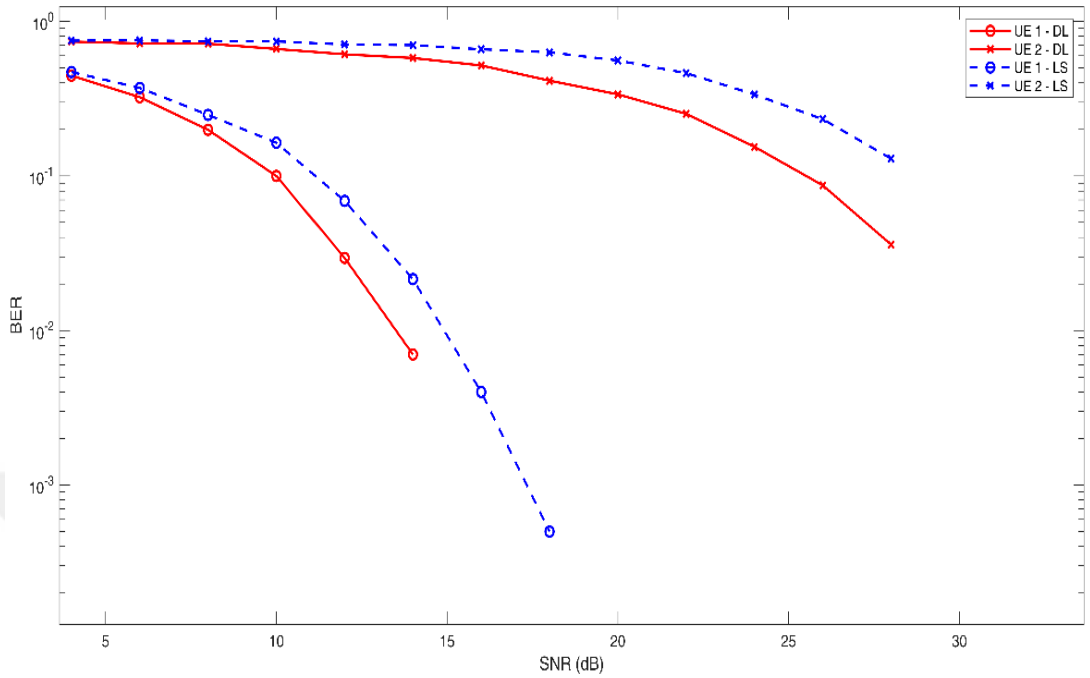

Figure 20. BER for two users DL/NOMA system compared with LS technique (NUM_{SC} =64).

For the same pilot subcarrier number, the BER for both DL network and ML is shown in figure 21. In this case the BER for DL based system is better than ML.

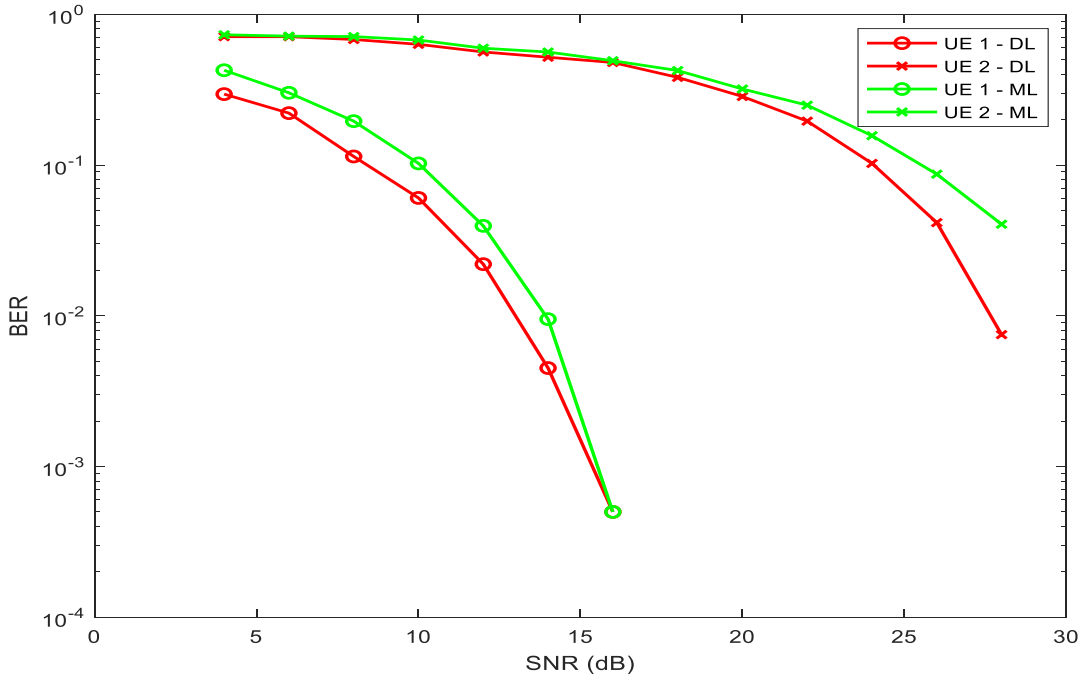

Figure 21. BER for two users DL/NOMA system compared with ML technique (NUM_{SC} =64).

Now figure 22 shows the BER curves for both DL network and MMSE. Again the BER for DL based system is better than that for MMSE based system.

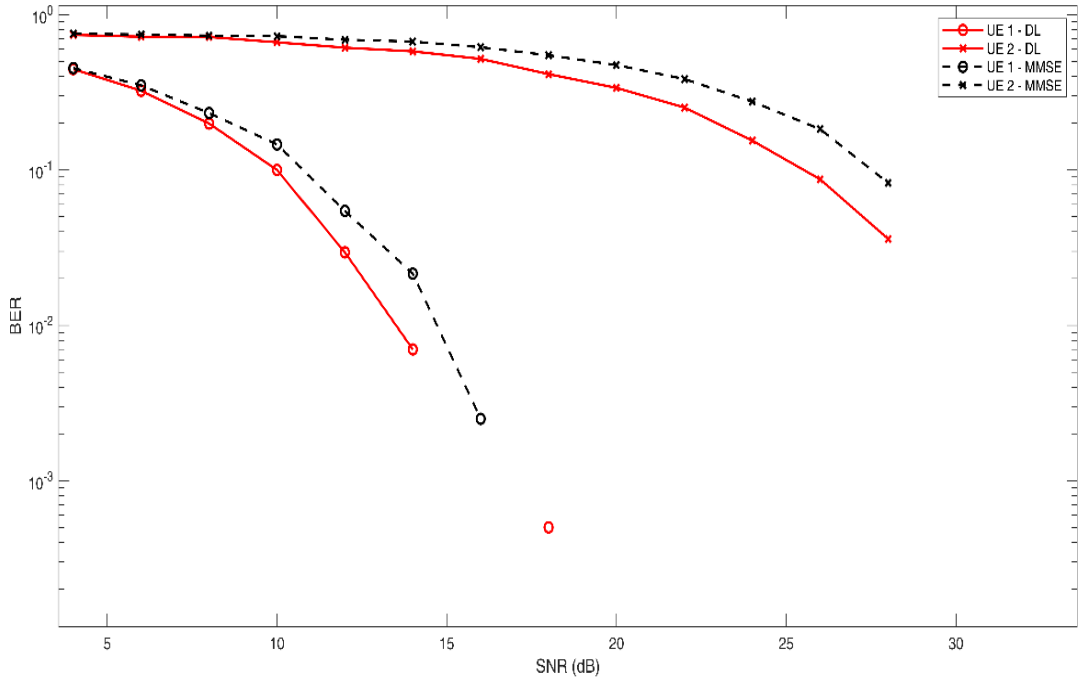

Figure 22. BER for two users DL/NOMA system compared with MMSE technique (NUM_{SC} =64).

The effect of changing the pilot subcarrier to be 16 is shown in figures (27 - 29) respectively. Figure 23 shows the BER for both DL network and LS in case of 16 pilot subcarrier.

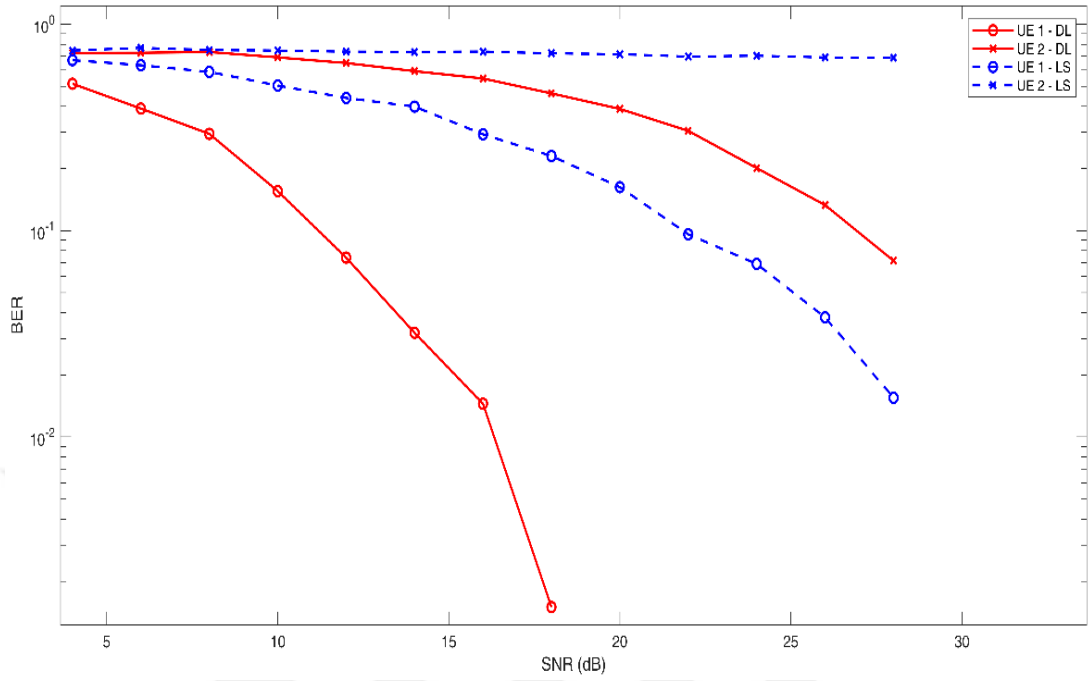

Figure 23. BER for two users DL/NOMA system compared with LS technique (NUM_{SC} =16).

BER curves for both DL network and ML in case of 16 pilot subcarrier are shown in figure 24.

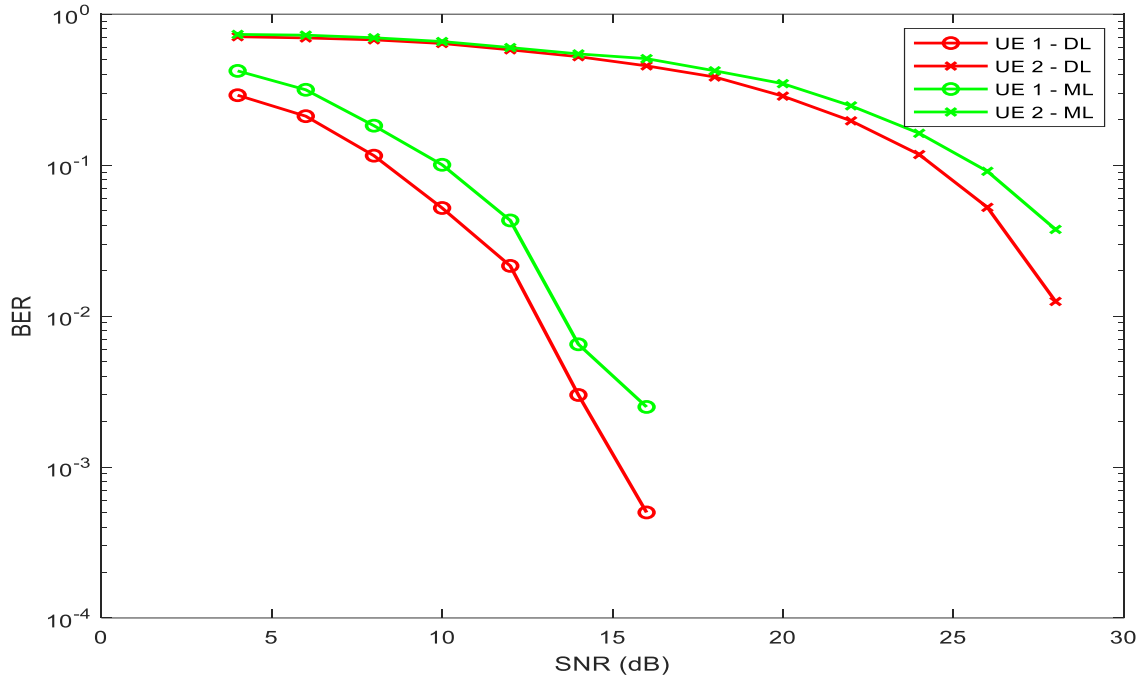

Figure 24. BER for two users DL/NOMA system compared with ML technique (NUM_{SC} =16).

The BER behavior for DL still better than that for ML even when the pilot subcarrier number is changed as shown in figure 25.

For all simulated cases DL is better than LS, ML and MMSE regardless the number of pilot subcarrier that has no significant effect on the BER for all simulated cases.

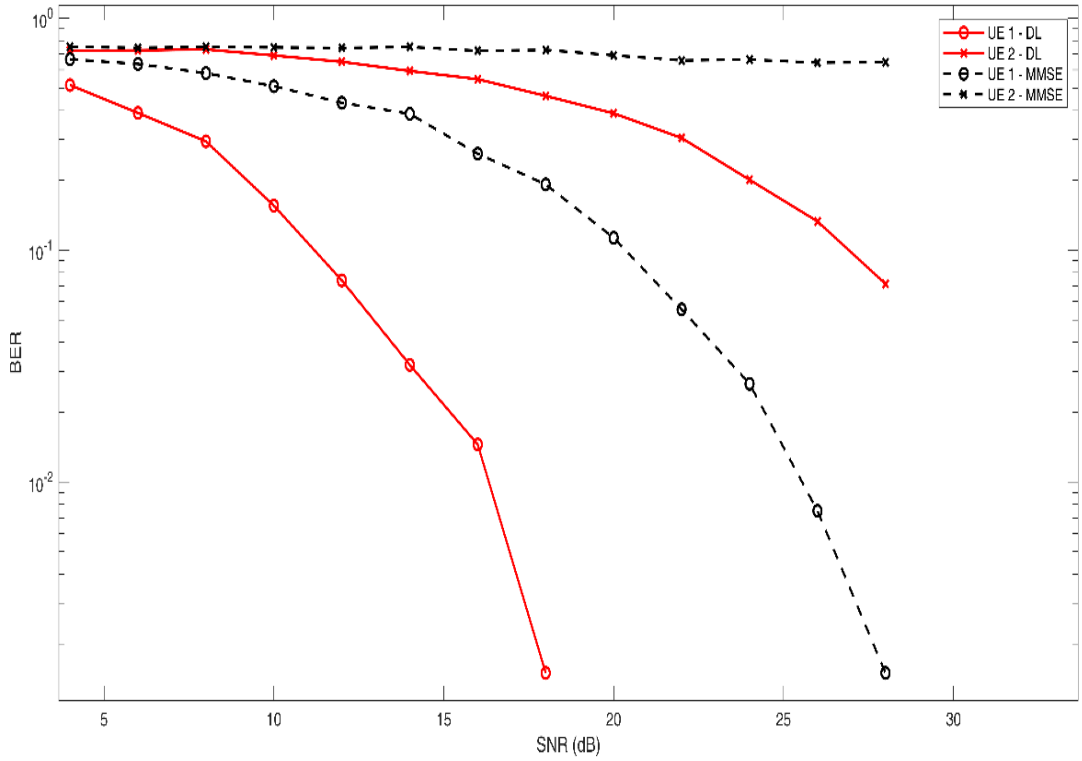

Figure 25. BER for two users DL/NOMA system compared with MMSE technique (NUM_{SC} =16).

CHAPTER FIVE

CONCLUSIONS AND FUTURE WORKS

Conclusions

In this study, a NOMA communication system for multiple users is simulated and the impact of power allocation on the bit error rate (BER) is analyzed. For a two-user NOMA system, enhancing the power allocation for any user while keeping the second user's allocation constant resulted or varying both power allocations for the two users results in improved system performance, evidenced by a reduction in BER for both users. In the subsequent simulation phase, a DNN is developed, trained, and evaluated as an alternative to the classical NOMA communication approach. This DNN aims to recover transmitted symbols for both users simultaneously. Figures illustrating BER curves for both users are plotted for each methodology, considering Signal-to-Noise Ratio (SNR) and transmitted power.

In the thesis phase of the simulation, a deep neural network is formulated, trained, and evaluated as an alternative to the NOMA communication system. A comparative analysis is conducted between the achievements of the deep neural network and the conventional NOMA system. This simulation encompasses three distinct NOMA operational scenarios. The comparison involves assessing the bit error rate (BER) for the deep neural network, as well as for NOMA using maximum likelihood (ML), least square error (LS), and minimum mean square error (MMSE) techniques.

Graphs depicting the bit error rate (BER) curves for both users are generated for each methodology as a function of signal-to-noise ratio (SNR). This enables an evaluation comparison between deep neural networks and traditional NOMA communication systems. The deep neural network exhibits superior outcomes as compared to the LS, ML, MMSE adaptive methods.

Future works

Many points of view are recommended as a future work that may enhance the NOMA systems and their performances. These consolidated recommendations cover key aspects such as

adaptability, efficiency, scalability, energy efficiency, security, and practical implementations. Some of these are:

1. Dynamic Power Allocation Algorithms: Develop dynamic power allocation strategies for NOMA systems that can adapt to changing network conditions, providing optimal power distribution and improving overall system characteristics.

2. Machine Learning Integration: Explore the integration of machine learning techniques into NOMA communication systems to enhance symbol recovery and efficiency. Investigate advanced algorithms, potentially combining deep learning with NOMA for improved performance.

3. Scalability and Network Efficiency: Evaluate the scalability of NOMA systems for larger networks with an increased number of users. Address challenges related to scalability and explore solutions for efficient resource allocation to support a growing number of users.

4. Energy-Efficient NOMA Systems: Focus on enhancing the energy efficiency of NOMA systems. Investigate power-efficient algorithms, optimize hardware components, and explore energy harvesting techniques to ensure sustainable and energy-efficient communication.

5. Security and Privacy Considerations: Address security and privacy concerns in NOMA systems. Investigate potential vulnerabilities and develop solutions to ensure secure and private communication, especially in sensitive applications.

6. Real-World Implementations and Interference Management: Conduct real-world implementations or field trials of NOMA systems to validate simulation results and assess the feasibility of deploying NOMA in practical communication scenarios. Explore advanced interference management techniques, particularly in environments with high user density.

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RESUME

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