Chapter 1 INTRODUCTION

1.1 Background

The scarcity of spectrum resources is a significant barrier to the advancement of wireless communication. Therefore, efforts to enhance spectral efficiency have become a critical challenge in both academic research and industrial innovation. To address this issue, many potential technologies have been explored to improve spectrum utilization, with Non-Orthogonal Multiple Access (NOMA) emerging as a promising solution [1]. Compared to orthogonal multiple access (OMA), NOMA increases overall system throughput by simultaneously serving multiple users within the same spectrum resources [2]. Additionally, NOMA shows great potential in supporting massive connectivity with high data rates, making it a strong candidate for next-generation wireless systems [3].

Despite its considerable advantages, one significant problem to the seamless adoption of NOMA lies in its complex receiver design [4]. Particularly when it comes to multiuser detection that plays a crucial role in NOMA to recover transmitted symbols from multiple users sharing the same resources. Traditional multiuser detection techniques, which require checking each constellation point one by one, face challenges in handling the interference caused by overlapping signals from different users. As the number of users is increase, the computational complexity of these techniques are also exponentially increase. Addressing the issue of receiver complexity has thus become a key area of research within the NOMA framework, with the objectivity of fully realizing NOMA's capabilities in advanced wireless communication systems for the next generation [5].

Iterative Spatial Demapping (ISM) [6] is a demapping technique designed to enhance the demodulation process over fading multiple access channels by exploiting the correlation between two sources. ISM is responsible for demapping the superimposed received signals from two sources on a symbol-by-symbol basis. To achieve this, ISM relies on *a priori* information in the form of Log-Likelihood Ratios (LLRs). By employing ISM it is possible to create a near match between the EXIT curves of the decoder and demapper, resulting a performance gap within the theoretical Slepian-Wolf/Shannon limit between

1.83 and 3.01 dB. However, it is important to note that when dealing with more than two users, the complexity of ISM increases along with the number of user involved, presenting challenges is scalability.

In recent years, Artificial Intelligence (AI) technology has expanded beyond traditional applications like pattern recognition, image processing, and edge computing, finding new roles in the classification of communication signals [7]. Within this domain, deep learning, a subset of AI, has been widely implemented into NOMA systems. Deep learning is great for fixing problems in wireless communication systems like synchronization, channel estimation, iterative decoding, and multiuser decoding [8] because it is very good at classifying and recognizing things. Deep learning's ability to learn intricate patterns and disentangle superimposed signals, along with its capacity to manage nonlinear relationships between transmitted symbols, makes deep learning exceptionally well-suited for enhancing the performance of NOMA systems.

The deep learning algorithm is implemented using a neural network, which composed of three main layers: input layer, output layer, and hidden layers. When multiple hidden layers are placed between the input and output layers, the system is called Deep Neural Network (DNN) [9]. Each layer within the network layer contains processing units known as neurons. These neurons work together to interpret input data, allowing the system to recognize and learn important features an patterns that can be used to solve complex problems. One of the key advantages of deep learning is its ability to facilitate end-to-end learning, enabling the system to directly map received signals to demapped symbols without the need for on intermediate steps. This streamlined approach not only reduces the need for explicit feature engineering but also simplifies the overall system design, making it more efficient [10].

In grant-free uplink NOMA networks, researchers [11] propose deep learning-aided multiuser detection technique known as DeepMuD. Compared to the traditional multiuser detection schemes, DeepMuD performs well in terms of BER. Additionally, DeepMuD offers grant-free access by allowing signal detection to be conducted on any number of IoT devices. A separate channel estimation technique is not required because the DeepMuD recognizes signals based on pilot responses. This highlights the effectiveness of DeepMuD in joint signal detection as well as its potential for application in other advanced physical layer techniques.

Another study about the application of deep learning in NOMA systems is [12], which proposes a DNN multitask framework for NOMA. This framework includes three key components: (i) channel module, (ii) multiple access signature mapping module (DeepMAS) designed to reduce implementation complexity, and (iii) a multiuser detection module (DeepMUD), which replaces traditional Interference Cancellation (IC) techniques for signal detection. The research found that this framework achieved a 50% reduction in both training loss and message error rate compared to traditional frameworks. Additionally, it showed an average SNR gain of 0.3 dB over traditional end-to-end frameworks, highlighting the effectiveness of deep learning-based optimization in NOMA systems.

This thesis introduces a novel approach for multiuser detection in NOMA systems, by utilizing deep learning as an alternative to traditional demapping techniques. By integrating deep learning into the demapping process, this thesis aims to simplify the receiver's process, making the system more efficient and less resource-demanding. The proposed deep learning model is trained to separate and predict the transmitted symbols of two users from superimposed received signals. This is achieved through a comprehensive training dataset that simulates various signal conditions, enabling the model to learn the intricate patterns and correlations inherent in NOMA signals. This approach not only simplifies the receiver's complexity but also enhances the overall performance of NOMA systems.

1.2 Problem Definition

NOMA is required to serve a communication network where the number of users is more larger than the number of resources. This condition causes a serious interference problem due to the limited resources. One of the main problem is the computational process required in the NOMA system that consume time and power. It is because the NOMA uses demapper, where the Euclidean distance of the all constellation point should be measured one-by-one to the received symbol for possible demapping or decoding. The calculation complexity is exponentially increasing when the number of users also increasing and higher order modulation are involved.

1.3 Research Objectives

To overcome the problem described in Section 1.2, the focus of this research is on the design of a deep learning-based demapper for NOMA system. The objectives of this study are as follows:

1. Develop a deep learning-based demapper for NOMA to eliminate the need to check each constellation point individually.
2. Evaluating the demapping results of two users of NOMA using the minimum complexity of feed forward neural network.
3. Prepare the minimum number of the required training dataset.
4. Design the minimum number of hidden layers and neurons.

1.4 Scope of Work

To narrow down the focus of this research, the scope of the problems addressed includes:

1. The NOMA dataset used in this thesis is generated through computer simulation involving two user over an Additive White Gaussian Noise (AWGN) channel.
2. Both uncoded and coded NOMA schemes are explored in this research.
3. The coded NOMA scheme employs Binary Phase Shift Keying (BPSK) modulation, repetition coding, and interleaver, while the uncoded scheme utilizes only BPSK modulation.
4. Iterative Spatial Demapping is used as the source data for generating the deep learning training dataset.
5. The deep learning dataset is collected with a SNR range of $0 - 20$ dB for both the uncoded scheme and the coded scheme.
6. Neural network algorithm is used as deep learning-based demapper for NOMA.
7. This thesis evaluates all the performances of the proposed system using a series of computer simulation.

1.5 Research Design

This thesis is divided into 4 work packages (WPs), each focusing on a specific aspect of this research. These WPs form a comprehensive study to produce high-quality results.

1. WP1: Study on non-orthogonal multiple access.

   This thesis studies the non-orthogonal multiple access system from academic publications, textbooks, and other thesis or dissertation books. This literature study involves an understanding of the fundamental principles of NOMA, its advantages and challenges.

2. WP2: Study on Iterative Spatial Demapper (ISM).

   This thesis also studies ISM as the traditional demapping technique for NOMA. Studying how ISM works, its current applications, and limitations, particularly in the context of multiuser detection.

3. WP3: The design of deep learning-based demapper.

   This thesis aims to develop a deep learning model that can efficiently decode superimposed received signals in NOMA system by leveraging the pattern recognition capabilities of deep learning.

4. WP4: Performance evaluations of the proposed deep learning model.

   This thesis compared the performance of the proposed deep learning-based demapper with the traditional ISM demapper under various scenarios through computer simulations.

1.6 Thesis Structure

This sub-chapter presents an overview structure of this thesis, highlighting the key sections and its respective contents. This thesis is organized as follows:

- **CHAPTER 2: BASIC THEORY**

  This chapter describe the fundamental concepts related to NOMA, ISM, and Deep Learning.

- **CHAPTER 3: THE PROPOSED DEEP LEARNING-BASED DEMAPPER**

  This chapter describes the specific systems of this research. It covers the simulation scenario, NOMA system model, deep learning training dataset, deep learning training and testing process, and details about the proposed deep learning.

- **CHAPTER 4: PERFORMANCE EVALUATION OF DEEP LEARNING-BASED DEMAPPER**
  This chapter presents the simulation results and provides a thorough analysis of the proposed deep learning-based demapper.

- **CHAPTER 5: CONCLUSION AND FUTURE WORK**
  The final chapter summarizes the research findings, draws conclusions, and suggests potential directions for future studies.