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COMPARISON OF DEEP LEARNING AND CONVENTIONAL RECEIVER DESIGN FOR A NOMA OFDM SYSTEM

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ABSTRACT

COMPARISON OF DEEP LEARNING AND CONVENTIONAL RECEIVER DESIGN FOR A NOMA OFDM SYSTEM

As the number of users and applications increases, wireless networks are crowded with massive amounts of data traffic in the near future, with the number of users increasing. Conventional Orthogonal Multiple Access (OMA) technologies such as OFDM and MIMO will not be enough to serve users efficiently. In 5G networks, Nonorthogonal Multiple Access (NOMA) is considered to be an effective solution to this issue. NOMA can increase spectral efficiency and user fairness of mobile communication networks. However, NOMA signals need to be processed using computationally expensive receiver structures. First the channel experienced by all users in the system needs to be estimated. Then the receiver needs to process all users' signals using an iterative multi-user receiver algorithm such as Successive Interference Cancelation (SIC). The computational complexity incurred does not always mean perfect demodulation because of complications such as imperfect knowledge of the channels state (CS) in the transmitter, frequency offset and phase jitter for multiple users and interference from multiple sources. Deep Learning (DL) has been used recently in many different applications involving large amounts of data. In this thesis it is applied to the design of a NOMA-OFDM system receiver.

Keywords: Non-orthogonal multiple access (NOMA), Orthogonal Frequency Division Multiplexing (OFDM), Deep Learning (DL) , channel estimation, equalization.

KISA ÖZET

BİR NOMA OFDM SİSTEMİ İÇİN DERİN ÖĞRENME İLE GELENEKSEL ALICI TASARIMININ KARŞILAŞTIRILMASI

Kullanıcı ve uygulama sayısı arttıkça, kablosuz ağlar yakın gelecekte çok büyük miktarda veri trafiğiyle dolup taşacak ve kullanıcı sayısı da artacaktır. OFDM ve MIMO gibi geleneksel Ortogonal Çoklu Erişim (OMA) teknolojileri, kullanıcılara verimli bir şekilde hizmet vermek için yeterli olmayacaktır. 5G ağlarında, Ortogonal Olmayan Çoklu Erişim (NOMA) bu soruna etkili bir çözüm olarak kabul edilir. NOMA, mobil iletişim ağlarının spektral verimliliğini ve kullanıcı adaletini artırabilir. Ancak NOMA sinyallerinin hesaplama açısından pahalı alıcı yapıları kullanılarak işlenmesi gerekir. Öncelikle sistemdeki tüm kullanıcıların deneyimlediği kanalın tahmin edilmesi gerekir. Ardından alıcının, Ardışık Girişim Önleme (SIC) gibi yinelemeli çok kullanıcılı bir alıcı algoritması kullanarak tüm kullanıcıların sinyallerini işlemesi gerekir. Ortaya çıkan hesaplama karmaşıklığı, vericideki kanal durumunun (CS) kusurlu bilgisi, birden fazla kullanıcı için frekans kayması ve faz titreşimi ve birden çok kaynaktan gelen parazit gibi komplikasyonlar nedeniyle her zaman mükemmel demodülasyon anlamına gelmez. Derin Öğrenme (DL), son zamanlarda büyük miktarda veri içeren birçok farklı uygulamada kullanılmaktadır. Bu tezde DL ile NOMA-OFDM bir sistem alıcısı tasarlanmıştır.

Anahtar Kelimeler: Ortogonal olmayan çoklu erişim (NOMA), Ortogonal Frekans Bölmeli Çoğullama (OFDM), Derin Öğrenme (DL), kanal tahmini, eşitleme.

ACKNOWLEDGMENT

I want to thank everyone who helped me reach this achievement,

My family and my professor, Thank you …………..

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ABBREVIATIONS

DL**:** Deep Learning

ML: Machine Learning

NOMA: Nonorthogonal Multiple Access

OMA : Orthogonal Multiple Access

5G: Fifth generation

FFT: fast Fourier transform

IFFT: Inverse Fast Fourier Transform

CP: cyclic prefix

SIC: Successive Interference Cancelation

ADC: Analog-to-digital converter

S/P: serial to parallel

P/S: parallel to serial

MIMO: multiple-input and multiple-output

SINR: Signal to interference noise ratio

SNR: Signal to noise ratio

ISI: inter symbol interference

OFDM: Orthogonal frequency-division multiplexing

OFDMA: orthogonal frequency-division multiple access

BER: bit error rate

LMMSE: Linear Minimum Mean Square Error

MMSE: Minimum Mean Square Error

QPSK: Quadrature Phase Shift Keying

QAM: Quadrature amplitude modulation

IOT: internet of things

AWGN: Additive white Gaussian noise

CCI : Co-Channel Interference

ICI: intra-cell interference

NN: Neural Networks

CNN: Convolutional Neural Networks

RBM: Restricted Boltzmann Machines

M2M: Machine-to-machine communications

LSTM: Long Short Term Memory

INTRODUCTION

1.1. The motivation of thesis

It has been shown in cellular communication systems that the communication system capacity of the network is limited by interference. In 2G systems the goal was to ensure orthogonality between users in different cells and in the same cell by not reusing frequencies in adjacent cells, and within each cell giving each user their own time slot in the time division multiple access (TDMA) system. In 3G and 4G communication, frequency reuse in adjacent cells was allowed while within each cell users were still orthogonally separated. More sophisticated receiver algorithms and modulation schemes such as multiple antenna systems known as multiple input multiple output (MIMO) and orthogonal frequency division multiple access (OFDMA), allowed high throughput despite higher interference.

In 5G wireless systems non-orthogonal multiple access (NOMA) has been introduced in addition to orthogonal multiple access techniques such as OFDMA. Even more sophisticated receiver technologies allow signals from multiple users to be decoded despite significant interference from within the cell as well as outside the cell. The combination of NOMA with OFDMA and MIMO significantly increases the throughput available in modern cellular systems.

To sustain high throughput, different communication receiver technologies are under investigation in addition to maximum likelihood (ML) receivers. The deep learning (DL) method is shown to achieve better results than ML but at a higher computational complexity. Comparing LMMSE to DL, the computational complexity difference decreases as the number of users, the number of OFDM carriers increases.

ML estimation becomes more expensive computationally as the constellation size increases. This means that DL has potential as a method for the more complicated communication systems of the future.

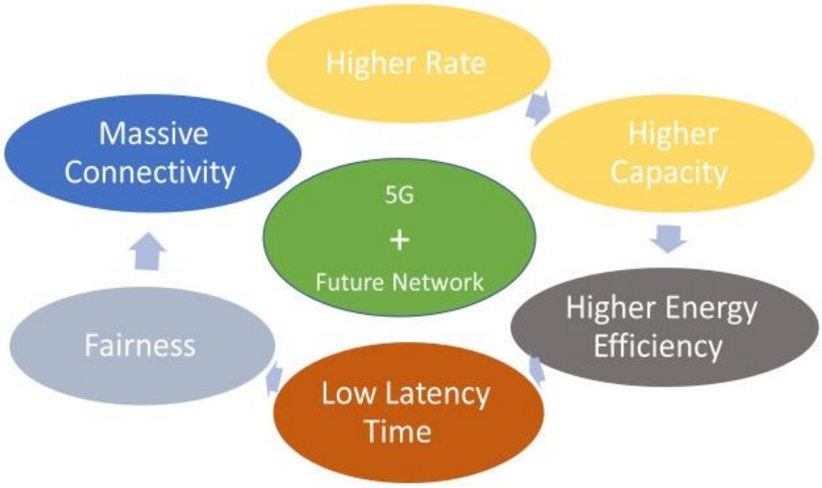

Figure I.1. Requirements of 5G and Future Wireless Networks.

1.2. Problem definition

In this thesis we design a deep learning based receiver for a NOMA-OFDM system. The receiver uses training 5G communications and channel estimation and signal detection and compare the Deep Learning (DL) receiver to conventional Maximum Likelihood (ML) and Linear Minimum Mean Square Error (LMMSE) receivers with ML channel estimation.

1.3. Research objectives

1) To model an NOMA - OFDM cellular system.

2) Comparing the performance of DL receiver with conventional ML and MMSE receivers

NOMA – OFDM SYSTEMS

2.1. Introduction

Non-orthogonal multiple access (NOMA) has been standardized in fifth generation (5G) wireless systems to allow more users, higher throughput and new applications in next generation wireless networks. NOMA will support the larger volumes of data that will be transmitted as more applications such as internet of things (IoT), hyperphysical systems are adopted more widely [1] [2]. When the NOMA scheme and orthogonal frequency division multiplexing (OFDM) technique are combined, the system achieved a better spectral efficiency [3]. In theory orthogonal multiple access (OMA) techniques can to avoid the intra-cell interference (ICI) completely, but it practice transmitter and receiver nonlinearities, synchronization errors and channels can break the orthogonality of transmitted waveforms. Further orthogonal multiple access does not has a robust requirement and the distance between re-used channels must be suitable. But this leads to an increase in cellular spectrum consumption, and this leads to a decrease in cellular spectral efficiency. However, due to the increase in the demand for the Internet-of-things (IoT) and the mobile communication this lead to more robust requirements for the next generation of wireless communication systems. These requirements involve massive connectivity and huge spectral efficiency. NOMA, which has massive connectivity, is capable to deal with simultaneous users through nonorthogonal resource allocation. Unlike conventional OMA, NOMA achieve overloading at the cost of acceptable receiver complexity increase by allows controllable interferences [4] [3] [5].

In orthogonal frequency-division multiplexing (OFDM) systems, the wideband communication channel is divided into smaller narrowband subcarrier channels. In most existing communication systems, these subcarrier channels are shared between multiple users using orthogonal frequency-division multiple access (OFDMA). In OFDMA each subcarrier is allocated to a single user at any point in time. As the demand for video, games and interactive services has increased on mobile networks, there has been a demand for even more bandwidth. In 5G this has led to the introduction of NOMA, where subcarriers allocated to more than one users at the same time. There are two flavors of NOMA. In power-based NOMA a user with higher received power is paired with a user with lower received power. The power difference allows the system to differentiate between the users. In cognitive radio NOMA, there is a primary user in the system with a guaranteed signal quality. The secondary user of the system will transmit with lower power so as not to interfere with the primary user. In the first system the stronger user is decoded first to ensure minimum probability of error for both users. In the latter system the secondary user is decoded first to ensure lower probability of error for the primary user of the system. As the signals from multiple users are received simultaneously the receiver of the NOMA system has to do a significantly good job to differentiate these signals. NOMA is frequently used with successive interference cancellation (SIC) receivers. In SIC users' signals are decoded one at a time and subtracted from the sum signal [6]. Pilot signal tones can be used to estimate the channel coefficients for all users using least squares (LS) or minimum mean square error (MMSE) estimators. In turn the estimates of the channel are used to estimate the unknown data channels. Much recent work has focused on NOMA system planning and resource allocation, channel state estimation [7] and signal estimation.

2.2. PREVIOUS STUDIES

In NOMA systems multiple users transmit across the channel, simultaneously. This concept is sometimes also referred to as having primary/secondary users or an underlay/overlay communication system. Having multiple users transmit on the same channel will mean that the signals interfere, so there needs to be a way to separate these signals. There are fundamentally two types of NOMA based on how users can be separated: code domain NOMA and power domain NOMA.

Power domain NOMA takes advantage of the fact that different users transmit with different powers, so the power difference allows the signals to be decoded accurately using a Successive Interference Cancellation (SIC) receiver.

Code domain NOMA is actually a group of techniques where diversity is introduced through non-orthogonal spreading codes which allow multiple users to be discerned using sophisticated receivers.

Narengerile and J. Thompson [8] investigated deep learning for channel estimation and signal detection in an OFDM-NOMA system with two users. They proposed to use deep learning for symbol estimation in their NOMA receiver. They showed promising results for their DL algorithm. This work differs from their work in several ways. First power allocation is used to differentiate NOMA signals. Second, the DL algorithm uses as input only neighboring subcarriers for each carrier. This significantly reduces the size of the neural network used and reduces the amount of data needed to train the system. Training in this work as with channel estimation, uses only the pilot subcarrier data rather than relying on a pre-trained NN.

Swapna et. al. [9] follow a different approach where they perform channel estimation using convolutional neural networks (CNN) and linear interpolation. They then use the result for symbol estimation. They find that the CNN approach performs significantly better in the task of channel estimation.

Guan Gui et. al. [10] also investigated a deep learning aided NOMA scheme based on the Restricted Boltzmann Machines (RBM) [11] rather than convolutional neural networks (CNN) as in the previous example. The RBM processed the input signals and trained them by a Long Short Term Memory (LSTM) network. In this work the LSTM-aided NOMA system achieved better performance, again showing that neural networks and deep learning algorithms can be useful in receiver design.

2.3. NOMA – OFDM Systems Overview.

In 5G systems, due to the increased demand for bandwidth, it has been decided to use Non-Orthogonal Multiple Access (NOMA). In NOMA systems the all transmission frequencies are reused not only in adjacent cells but also within the same cell [2]. The goal is to choose which users will share spectrum intelligently to allow the best throughput for all users [12]. When OFDM is used, inter-symbol interference is very low since it can be eliminated using the cyclic prefix of the OFDM symbol. When multiple transmitted signals are interfering on a single received signal, there are some techniques which can be used to extract all signals [13] [14]. These are generally based on the fact that the transmitted symbols belong to a finite alphabet, and that channel coefficients change more slowly than the symbol rate. For instance if two signals are combined together in the form a s1 + b s2, and each user uses a QPSK constellation, so s1, s2 are elements of the set {1 + i, 1 – i, –1 + i, –1 – i }. This means that every received signal must be classified to be one of 16 possible signals, e.g. a (1 + i) + b (1 + i), a (1 + i) + b (1 – i), etc. From this classification it is possible to estimate the channel gain using training symbols.

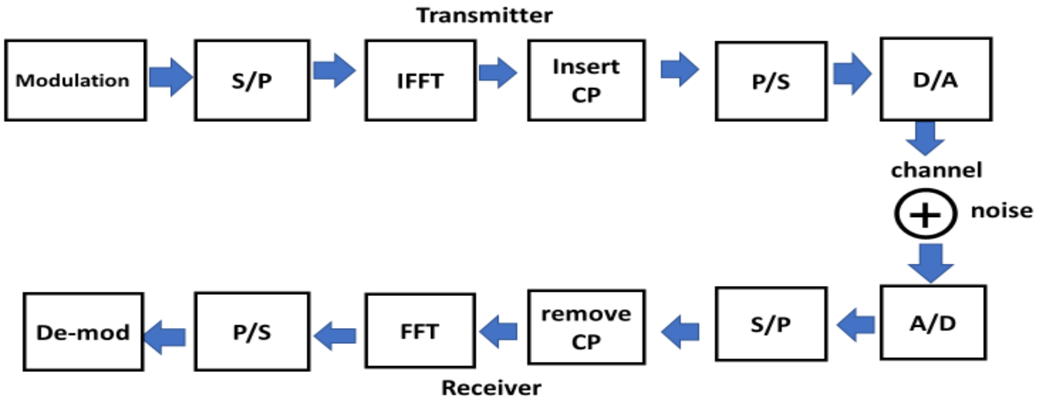

Figure II .1. OFDM Generation Block diagram.

Figure II..1 illustrates the OFDM system block diagram (the transmitter, fading channel and a receiver). The fast Fourier transform (FFT) and the inverse fast Fourier transform (IFFT) are used in the digital (time/frequency) implementation of the OFDM transmitter and receiver respectively [13] .

At the first the source will take the data (bits or integer) and it will convert the serial data into parallel. after that it will modulate the data by several modulation techniques (BPSK, QPSK, 16 QAM). Inverse Fast Fourier Transform (IFFT) will convert the signal from frequency domain into time domain, and the data will convert back to serial data by using **P/S** converter and it goes to the noise (fading) channel [13] [14].

The purpose of cyclic prefix (CP) is to suppress the Symbol Interference (ISI), Inter carrier Interferences (ICI), Co-Channel Interference (CCI)] [13]. Cyclic Prefix Make the symbol period longer by copying the tail and glue it in the front.

The receiver will do the opposite of the transmitter. Fast Fourier Transform (FFT) will convert the signal from the time domain into the frequency domain again [14].

2.4. NOMA VS OMA.

Orthogonal multiple access systems (OMA) are a technologies where radio resources assigned to each users in orthogonal (frequency and time) so they are not interfering [13]. The Orthogonal frequency-division multiple access (OFDMA) is an example on OMA systems. OMA objective to prevent interference between users and at the receiver side it has low complexity signal decoding. As well, the capacity of multi-user systems cannot always achieve by these orthogonal schemes [14] and in terms of spectral efficiency they are suboptimal.

NOMA differs from OMA in that it allows multiple signals to be superimposed on the same subcarrier [15] the successive interference cancellation (SIC) alleviate the received interference that happen because of the superimposed signals, as illustrated in Figure II.2 [1] [6]. The two colors represent the transmit power of two different users' signals. To make the interference low of the superimposed signals and to make successful decoding, the power of each signal should be completely optimized [16].

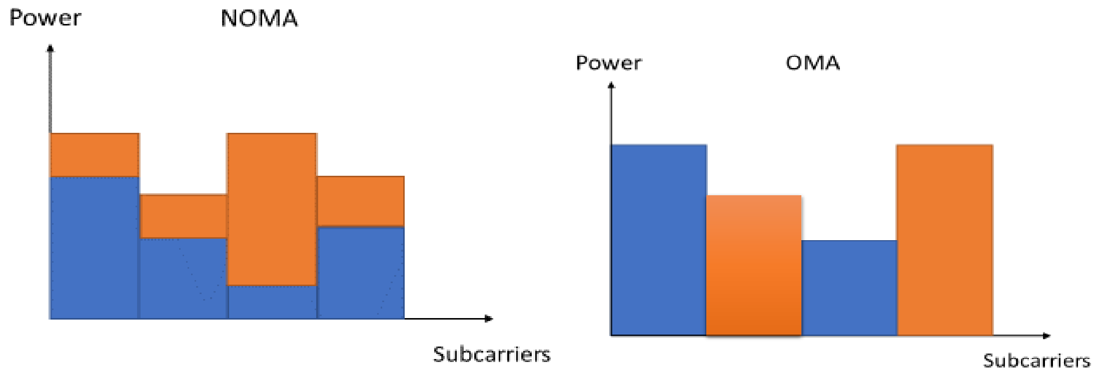

Figure II.2. OMA vs NOMA.

2.5. Hybrid OMA – NOMA Techniques.

In OMA - NOMA hybrid scheme, the users are divided into varied groups, on the available RB to transmission (i.e., bandwidth or time) to serve a group of users. Moreover, the users in the all groups are served based on power-domain NOMA technique, particularly, in these hybrid systems there are different advantages such as overhead reduction because of SIC at all users [17]. NOMA is better in spectrum and energy efficiency that can be more suited for Machine-to-machine (M2M) communications which is lower bandwidth values systems [13] [17].

2.6. Successive Interference Cancelation (SIC) .

The standard receiver algorithm for NOMA - OFDM systems is the Successive Interference Cancelation (SIC) algorithm. In SIC, the first step is to estimate the channel coefficients (a and b above), generally using training data [6]. Then the users are arranged in order of received power. In each stage the symbols belonging to the user with the highest power are demodulated. Next, the symbols are multiplied by that user's channel gain and received power, and subtracted from the sum received signal. The process is repeated until all users have been decoded [6] [16].

This method successfully reduced the interference level for users with lower power, improving their error rates.

$$y = h(t) * x_D(t) + n(t) \tag{0.1}$$

Where $h(t)$ is the channel impulse response, $x_D(t)$ is the unknown data sequence and $n(t)$ is white noise for user 2 but white noise plus the interference from user 2 for user 1.

We can write the channel convolution using the circular convolution matrix. But this time the channel is known and the user's signal is unknown. So we write the convolution as:

$$\begin{bmatrix} y(1) \\ y(2) \\ \\ \\ y(N) \end{bmatrix} = \begin{bmatrix} h(1) & h(N) & h(N-1) & \cdots & h(N-L+2) \\ h(2) & h(1) & h(N) & \cdots & h(N-L+3) \\ \vdots & \vdots & h(1) & & \vdots \\ & & & \ddots & h(N) \\ & & & & h(1) \\ h(N) & h(N-1) & & & \vdots \end{bmatrix} \begin{bmatrix} x(1) \\ x(2) \\ \vdots \\ x(N) \end{bmatrix} + \begin{bmatrix} n(1) \\ n(2) \\ \vdots \\ n(N) \end{bmatrix} \tag{0.2}$$

If the length of the channel impulse response L is less than N, then the remaining terms of the channel impulse response become zero.

As previously we write the equation as a vector matrix multiplication:

$$\vec{y} = H\ \vec{x} + \vec{n} \tag{0.3}$$

Then the linear MMSE estimator of the data vector x is :

$$\vec{\hat{x}} = \left(H^H H + \sigma^2 I\right)^{-1} H^H \vec{y} \tag{0.4}$$

In this case the algorithm for SIC is shown in Table II .1.

Table II .1. Successive Interferene Cancellation (SIC) Algorithm.

1. Estimate channel matrices for all users
2. Let k = 1.
3. Estimate the symbol transmitted by user k.

$$\vec{\hat{x}}_k = \left(H_k{}^H H_k + \sigma^2 I\right)^{-1} H_k{}^H \vec{y} \tag{0.5}$$

4. Subtract the effect of user k's data from the total received waveform:

$$\vec{y} = \vec{y} - H_k \vec{\hat{x}}_k \tag{0.6}$$

If there are any undecoded users left remaining, let k = k + 1 and return to step 3.

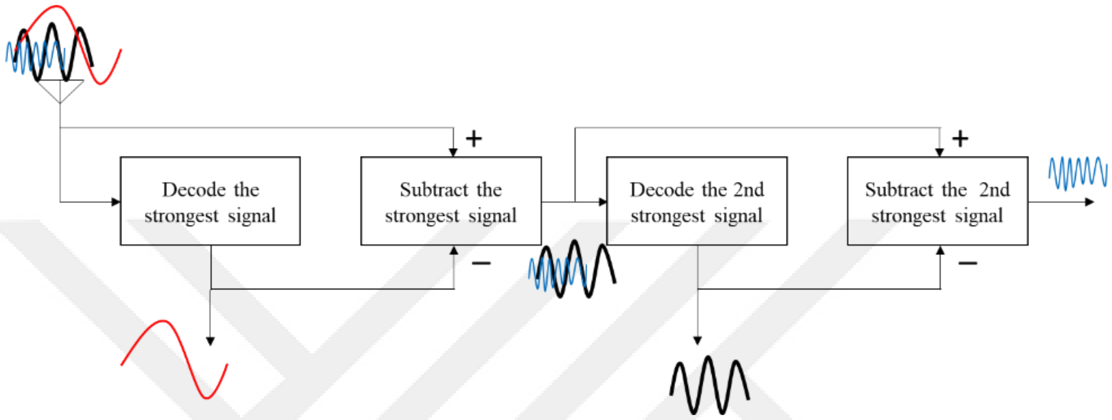

Figure II.3. Successive Interference Cancellation (SIC) receiver.

Consider the case when three different signals enter the channel as shown in Figure II.3. The signal at the input to the Successive Interference Cancellation (SIC) receiver contains the sum of all three signals. The SIC receiver first decodes the strongest signal from the group of users. It subtracts the strongest signal from the received signal. What remains is the sum of the 2nd and 3rd strongest signals. Then the system estimates the second strongest signal and subtracts that from the received signal. What remains is the weakest 3rd signal [1] [16]. This process can be repeated to get all the received signals, however its success depends on how well each signal can be estimated. The signal estimates are significantly better when the signal powers are very different, this is known as “power diversity”.

DEEP LEARNING AND CONVENTIONAL RECEIVERS

3.1. Deep Learning (DL) Concept :

Machine learning concepts and techniques have been used in communications for many years. Deep learning algorithms are machine learning algorithms based on neural networks with a deep structure. They became popular first in speech processing and image processing applications where they were found to outperform other machine learning algorithms significantly. This performance was attributed to the resemblance of the deep neural network to human cognitive structures [18] [19] [20] [21].

The combination of the linear structure of the neural network with the nonlinear functions of each network node allows gives superior performance in many complex tasks. The deep learning structure enables computers to learn to do what comes naturally to humans, who can often make instantaneous decisions based on complex input which turn out to be mostly accurate if not perfectly so. A typical example is the ability to read handwritten letters and numbers. Similarly while a restaurant owner can provide real time service to many customers even when the number of tables and food servers is limited, but it takes complicated algorithms to accomplish the same thing using machine intelligence.

Deep learning is characterized by the potential to make a learning model at several levels. The neural networks used in deep learning involve tens or even hundreds of successive layers, and through exposing them to training data they are learning automatically by adjusting the coefficients of the links between the networks to obtain the correct results. The combination of linear sums at the input to the NN and the nonlinear node functions mean many functions can be implemented by the NN, based on the parameters which are trained by data. Most machine learning algorithms by contrast are based on an underlying mathematical model of the problem being solved, which means that the rules for finding the solution are hard coded into the algorithm.

Table III 1. Machine Learning (ML) VS Deep Learning (DL).

Machine Learning (ML)	**Deep Learning (DL)**
ML algorithms based on a model of underlying problem being solved.	DL uses an artificial neural network, requires only training input and output.
Rules are hard coded based on the model.	ANN structure allows many functions to be implemented, ANN learns correct rules from data.
Often requires (and is limited to) little or moderate amounts of data for training.	Needs a very large datasets for training.
Programmers define features of problem.	Features are generated by the NN, they correspond to output of each layer.
Programmers can define subproblems which are solved independently to improve implementation.	The parallel processing inherent in the ANN allows the problem to be solved in a single network.
Training is fast but implementation is often slower.	Training is slower but ANN structure means implementation is faster
Performance guarantees are possible since rules are known.	Performance guarantees not easy to obtain.

3.1.1. Neural Networks (NN)

Neural networks are built from neuron processing nodes. These nodes are arranged in layers which are connected by links. Each node performs a simple function, usually a nonlinear function whose output is between 0 and 1. The links from each layer to the next show the inputs to the function of each node. The links may also contain weights. During the training phase of the neural network these links and their weights are adjusted in order to approach the correct output for each data point [19] [21].

A typical neural network consists of multiple layers of neural processing nodes arranged in layers, with links between them. This architecture is shown in Figure III.1.

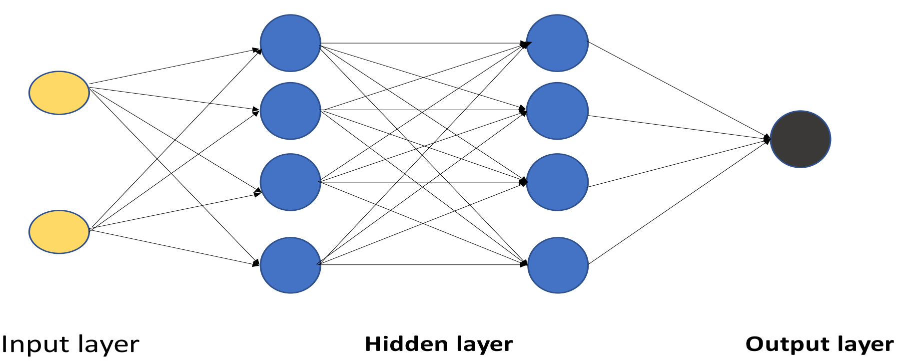

Figure III.1. Neural Network.

3.1.2. Types of Deep Learning

Machine learning algorithms are generally classified into three categories: supervised learning, unsupervised learning and reinforcement learning. Deep learning algorithms can be derived for all three classes.

In supervised learning algorithms the data comes with a well defined set of inputs and outputs, and the ANN is modified to produce the same output as the training data. Recurrent Neural Networks (RNN), Gated Recurrent Units (GRU), Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), and Long Short Term Memory (LSTM) can be used to generated supervised .

Unsupervised learning algorithms are given input data and a goal but not explicit lables. A typical problem addressed by unsupervised learning algorithms is clustering, in which the input data must be categorized into different classes, but the algorithm is not given the categories or even the number of categories. In this case the deep learning algorithm usually includes two stages, in the first stage the categories are identified. In the second stage the data is categorized.

Another unsupervised learning problem is dimensionality reductions, in which the goal is to represent many dimensional data using fewer dimensions. The number of dimensions that should be eliminated is unknown, the goal is to eliminate as many dimensions as possible. Dimensionality reduction is accomplished by neural networks known as autoencoders. Autoencoders aim to encode the data to a lower dimension, decode back to the higher dimension and use as a training function a mix of the reconstruction loss and the dimensionality reduction.

There is an in between class of learning algorithms called semi-supervised learning algorithms. These are mostly tasks for which supervised learning algorithms would be more appropriate, however labels are not available for all the training data.

In reinforcement learning the algorithm evolves and changes its parameters (or trains) as it is classifying data based on a reward function obtained from the classification. Reinforcement learning will be preferred if feedback is available from the environment after the learning algorithm is executed [19] [22].

3.1.3. Basic Deep Learning Models

Many types of neural network algorithms have been developed. Coşkun *et. al.* [24] present an overview of several popular neural network algorithms.

Convolutional Neural Network (CNN) are used for input data which is arranged in two (or more) dimensions. CNNs retain the spatial structure and relationships in the original data by having an input stage which applies two dimensional filters to the input data to obtain the input to the second stage. The input to the second stage then contains features such as edges which can be used to detect objects [21] [23].

Recurrent neural networks (RNN) are used for data which arrives in order, for instance time sequence data. RNNs retain time-dependent information of the input by storing the prior data inputs and using these past data in generating current output [22] [23].

Recurrent Convolutional Neural Networks (RCNN) also exist, these are useful for two-dimensional time sequence data such as video or MIMO channel measurements.

Autoencoders are a type of neural network most useful for unsupervised learning tasks, particularly compression. They will reduce the dimensionality of the input then try to recreate the original input from the reduced dimension data, the goal being to minimize the error between the original and the recreated input for some error criterion. This allows the NN to learn a dimensionality reduction projection – similar to principle component analysis (PCA) – without the mathematical foundation. Generally autoencoders only consists of a few layers, meaning that they do not use deep learning. However deep learning networks can be created by stacking autoencoders together.

Deep belief networks are another type of neural network architecture. They are produced by stacking multiple layers of Restricted Boltzman Machines (RBM) one after another. Restricted Boltzman Machines are actually very similar to autoencoders, but they are set up so that there is only an input and hidden node stage. After encoding instead of decoding to produce the original data at the output of the NN, the RBM calculates in reverse to get the same data at the previous node. The success of the calculation is determined using a cost function which is the entropy of the joint distribution between the variables in the hidden nodes and the visible nodes. This is used in place of the traditional backpropagation in other types of deep learning ANNs. So the decoding stage of the autoencoder is never realized, only the encoding stage, and multiple RBM can be stacked together to create the DBN.

In this thesis we use a convolutional neural network based receiver. This type of DL architecture was selected because the data is two dimensional in frequency and users and contains correlations particularly across frequencies, and because of NOMA the user-domain signal is also correlated.

3.1.4. Steps of Deep Learning

A. Dataset preprocessing

Dimension reduction happen in the data preprocessing stage, that include the models of machine learning. The preprocess is necessary because the data feature engineering is so complex. When performing deep learning to machine profile, the dimension decrease stage can be eliminate (if dimension is not too large) and can directly preprocessed the training dataset. the model is trained using the training set, and to evaluate the signal using the verification data set [19] [21] [23].

B. Model Selection and Training

To train the models a several of deep neural networks are used like (CNN, RNN).

C. Verification and Assessment

Various assessment frameworks are used to examine the efficient of the process or to establish the suitable parameters for the models [19] [25].

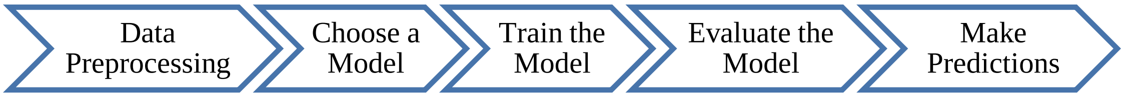

Figure III.2. Steps of Deep Learning.

3.2. Deep Learning (DL) Receiver

The alternative method is to use Deep Learning (DL) algorithms in a single step. DL is based on multi-stage neural networks with nonlinear activation functions. DL has recently been applied to many parts of the communication system, for resource allocation, channel estimation, and decoding. DL does not require a model and works in a single step. The same training data which is used for the SIC receiver is used to train the neural network to learn the coefficients which lead to the best identification of channel coefficients.

In designing the neural network, the number of states is taken to be the number of subcarriers, however symbol estimation for any carrier n uses as input only those carriers within 2 subcarriers of the target subcarrier, that is the joint estimation only uses the neighboring two subcarriers from each side. This reduces the computational complexity of the DL algorithm significantly without any loss of performance, since the effect of the channel in OFDM is mainly restricted to causing carrier interference between close subcarriers, and frequency offset can be well estimated from a sequence of five subcarriers.

3.3. Maximum Likelihood (ML) Receiver

An alternative to SIC is using Maximum Likelihood (ML) estimation of the symbols. In ML estimation, the received waveform is compared to all possible waveforms given the channel estimate, and mapped to the closest symbols. ML can be shown to achieve the capacity of the channel but can be very computationally expensive particularly as the constellation sizes and the number of users increases. It is also dependent on the channel estimate which is generated using the linear MMSE receiver. This means that errors in channel estimation will increase the probability of error for the ML receiver.

3.4. Linear Minimum Mean Square Error (MMSE) Channel Estimation

For the wireless channel.

$$y = h(t) * x_p(t) + n(t) \tag{0.1}$$

Where $h(t)$ is the channel impulse response, $x_p(t)$ is the pilot sequence and $n(t)$ is white noise.

We can write the channel convolution using the circular convolution matrix .

$$\begin{bmatrix} y(1) \\ y(2) \\ \\ y(N) \end{bmatrix} = \begin{bmatrix} x(1) & x(N) & x(N-1) & \cdots & x(N-L+2) \\ x(2) & x(1) & x(N) & \cdots & x(N-L+3) \\ \vdots & \vdots & x(1) & & \vdots \\ & & & \ddots & x(N) \\ & & & & x(1) \\ x(N) & x(N-1) & & & \vdots \end{bmatrix} \begin{bmatrix} h(1) \\ h(2) \\ \vdots \\ h(L) \end{bmatrix} + \begin{bmatrix} n(1) \\ n(2) \\ \vdots \\ n(N) \end{bmatrix} \tag{0.2}$$

Here we write the equation in matrix form using the circular convolution matrix.

$$\vec{y} = X\,\vec{h} + \vec{n} \tag{0.3}$$

Then the linear MMSE estimator of the channel vector h is .

$$\vec{\hat{h}} = (X^H X \; + \sigma^2 I)^{-1} X^H \vec{y} \tag{0.4}$$

SIMULATION

4.1. System Model

The system under consideration in this paper uses Orthogonal Frequency Division Multiplexing (OFDM) in downlink communication (from the base station to 2 users). In OFDM, the bandwidth available to the users is divided into many narrowband channels which are spaced precisely to ensure that the signals across these channels do not interfere, that is, that the channels are orthogonal.

In many modern communication systems such as LTE and IEEE 802.11 wifi networks the carriers are allocated to different users based on their channel conditions and the users' bandwidth requirements. Each carrier is allocated to a single user at any fixed time instant. This communication system is known as an OFDMA system. This does not however prevent all interference since all frequencies are reused in adjacent cells.

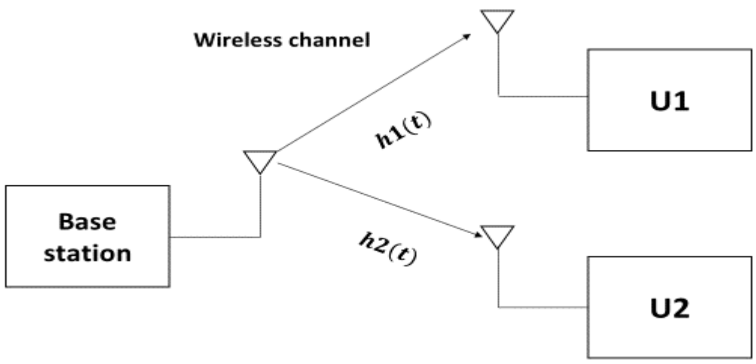

Figure IV.1. Two-user NOMA system.

The Signal to Interference and Noise Ratio (SINR) for user 1 in an OFDMA system can be written as:

$$\gamma = \frac{P_1 h_1}{\sum_{k=2}^{N} P_k h_k + \sigma^2} \tag{0.1}$$

In this equation P_k represents the transmission power for user k. Since our system looks at downlink communication $h_k = h_1$ is the channel gain for the signal belonging to user k. The channel gain is the same for all users' signals since they all traverse the same path from the base station to the mobile user.

4.2. Simulation and Results

This work have implemented an OFDM NOMA communication system with two users and 128 OFDM subcarriers in the Matlab simulation platform. Deep Learning, SIC-MMSE and Maximum Likelihood (ML) receivers have been implemented.

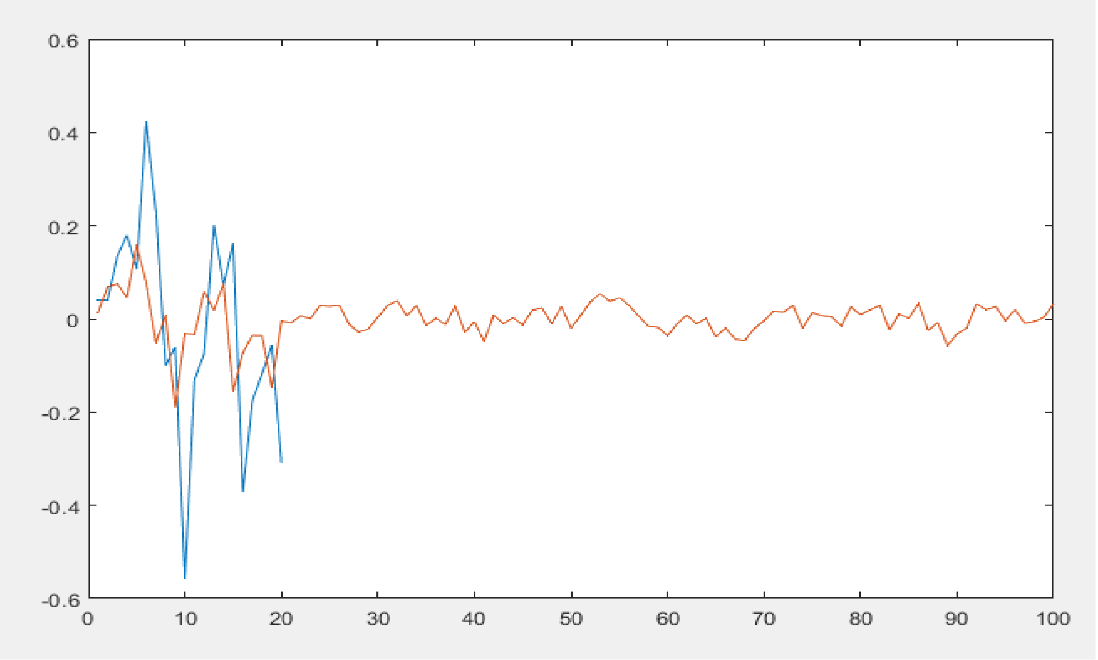

Figure IV.2. Test channel estimation.

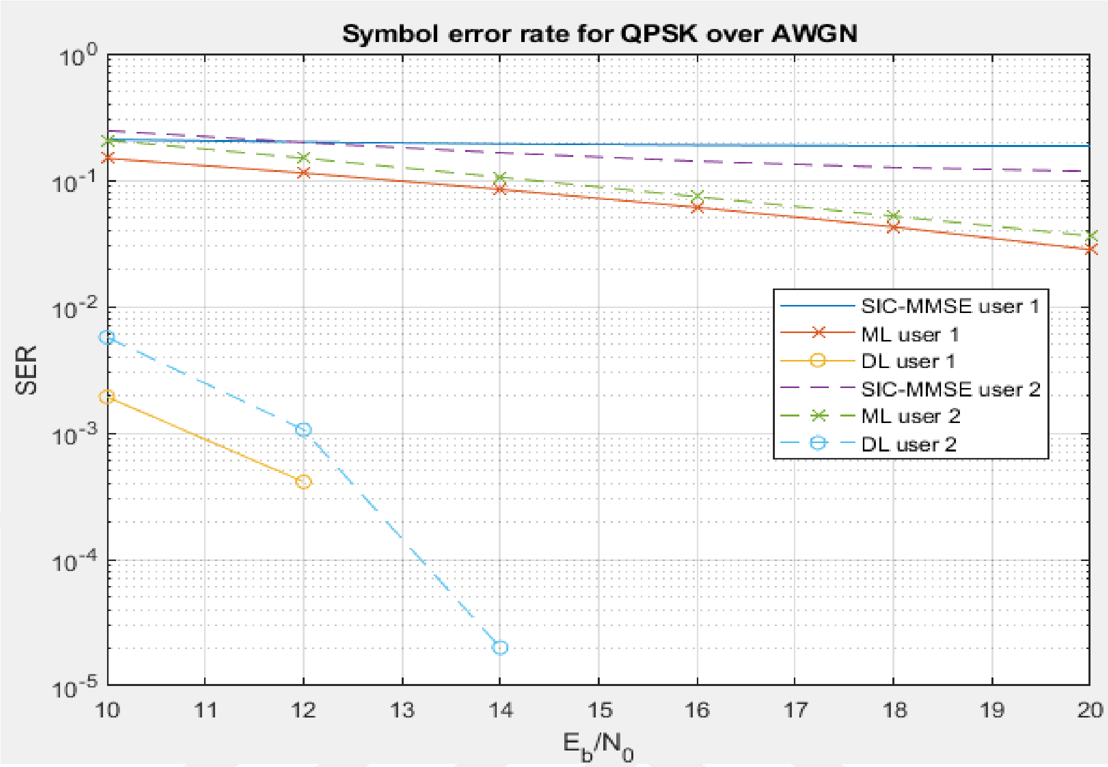

Figure IV.3. Simulation results.

Figure IV.3 shows the results of our simulation. The results have shown that for the same signal to noise ratio (SNR) the probability of error is significantly lower for the Deep Learning receiver than for the conventional receivers. This is mainly due to the more accurate channel estimation using the DL algorithm.

SUMMARY AND CONCLUSIONS

This thesis contains a mathematical analysis and simulation results from a NOMA OFDM system. Both maximum likelihood and deep learning receivers were implemented and the results were compared.

Deep Learning is able to use data more efficiently to accurately predict the channel matrix and result in a better match to transmitted symbols . The computational complexity of deep learning is larger in the beginning due to network setup costs, but the network requires only updating over time. The per carrier cost increases linearly with the number of neighbors included in the optimization times the number of carriers.

We will explored methods to further simplify deep learning algorithm to make it simpler and apply it to scenarios involving more communication links with larger data processing requirements and large amounts of data.

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