A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
OF ÇANKIRI KARATEKİN UNIVERSITY

SIGNAL DETECTION IN OFDM SYSTEMS FOR VISIBLE LIGHT COMMUNICATION BASED ON DEEP LEARNING

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF MASTER OF SCIENCE
IN
ELECTRICAL AND ELECTRONICS ENGINEERING

BY

YASIR IBADI HAMAD AL-MHALLAWI

ÇANKIRI

2022

SIGNAL DETECTION IN OFDM SYSTEMS FOR VISIBLE LIGHT COMMUNICATION BASED ON DEEP LEARNING

By Yasir Ibadi Hamad AL-MHALLAWI

December 2022

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ABSTRACT

SIGNAL DETECTION IN OFDM SYSTEMS FOR VISIBLE LIGHT COMMUNICATION BASED ON DEEP LEARNING

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In this thesis, for signal detection in orthogonal frequency division multiplexing systems, the deep learning neural network is utilize to classify symbols at the receiver. The symbol error rate and least square and minimum mean square error estimations are compare after the long short-term memory based neural network has been train for a single subcarrier. This initial trial's offline training and online deployment stages are anticipate using a fixed wireless channel. Each transmitted orthogonal frequency division multiplexing packet has a random phase shift performed to assess the neural network's stability.

2022, 44 pages

Keywords: Deep learning, Signal detection, OFDM, Visible light communication.

ÖZET

DERİN ÖĞRENMEYE DAYALI GÖRÜNÜR IŞIK İLETİŞİMİ İÇİN OFDM SİSTEMLERİNDE SİNYAL ALGILAMA

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Elektrik ve Elektronik Mühendisliği, Yüksek Lisans

Tez Danışmanı: Prof. Dr. Halil Tanyer EYYUBOĞLU

Aralık 2022

Bu tezde, ortogonal frekans bölmeli çoğullama sistemlerinde sinyal tespiti için, alıcıdaki sembolleri sınıflandırmak üzere derin öğrenme sinir ağı kullanılmıştır. Uzun kısa süreli bellek tabanlı sinir ağı tek bir alt taşıyıcı için eğitildikten sonra sembol hata oranı ile en küçük kareler ve minimum ortalama kareler hata tahminleri karşılaştırılmıştır. Bu ilk denemenin çevrimdışı eğitim ve çevrimiçi dağıtım aşamalarının sabit bir kablosuz kanal kullanması bekleniyor. İletilen her ortogonal frekans bölmeli çoğullama paketi, sinir ağının kararlılığını değerlendirmek için gerçekleştirilen rastgele bir faz kaymasına sahiptir.

2022, 44 sayfa

Anahtar Kelimeler: Derin öğrenme, Sinyal algılama, OFDM, Görünür ışık iletişimi.

PREFACE AND ACKNOWLEDGEMENTS

I would like to thank my thesis advisor, Prof. Dr. Halil Tanyer EYYUBOĞLU, for his patience, guidance and understanding.

Yasir Ibadi Hamad AL-MHALLAWI
Çankırı-2022

CONTENTS

LIST OF ABBREVIATIONS

ANN	Artificial neural network
AWGN	Additive white gaussian noise
BER	Bit error rate
BPSK	Binary phase shift keying
CNN	Convolutional neural network
CP	Cyclic prefix
DC	Direct current
DFT	Discrete fourier transform
DL	Deep learning
DNN	Deep neural network
FDM	Frequency division multiplexing
FEC	Forward error correction
FFNN	Feed forward neural network
FFT	Fast fourier transform
FSO	Free space optical
HF	High frequency
ICI	Intercarrier interference
IDE	Integrated development environment
IDFT	Inverse discrete fourier transform
IFFT	Inverse fast fourier transform
IR	Infrared
ISI	Intersymbol interference
IoT	Internet of things
LED	Light-emitting diode
Li-Fi	Light fidelity
LS	Least squares
LSTM	Long short-term memory
ML	Machine learning
MCM	Multicarrier modulation
MIMO	Multi input multi output
MSE	Mean square error
MMSE	Minimum mean square error
NN	Neural network
OFDM	Orthogonal frequency division multiplexing
OWC	Optical wireless communications
PAPR	Peak-to-average power ratio
PWE	Plane wave expansion
QAM	Quadrature amplitude modulation
QPSK	Quadrature phase shift keying
ReLU	Rectified linear unit
RF	Radio frequency
RGB	Red-green-blue
SER	Symbol error rate
SDMA	Space division multiple access

SFNs	Single frequency networks
SNR	Signal to noise ratio
SSE	Sum of squared errors
UV	Ultraviolet
VLC	Visible light communication
Wi-Fi	Wireless fidelity

LIST OF FIGURES

1 INTRODUCTION

Wireless technologies are the real exploshigh-rateions in the field of telecommunication. Wireless communication is growing rapidly because the necessity for reaching data anywhere at any time is rising heavily. The demand for reliable connectivity and high-rate data services is increasing which requires novel technologies. This is the rationale behind the increased interest in OFDM as a high-rate data transmission system in a frequency-selective fading channel. Wired and wireless communications both use the multi-carrier transmission method known as OFDM. This method divides the available frequency spectrum into a number of tightly spaced carriers, each of which is independently modulated by low-rate data streams. The close spacing of the carriers is facilitated by the orthogonality between the carriers (Verma *et al.* 2021, Bodkhe 2020).

Despite being a powerful modulation method, OFDM has its difficulties. The main issue with OFDM systems is their huge PAPR, which necessitates using power amplifiers with expansive linear ranges. The system's power efficiency decreases as a due to power amplifiers' increased back-off requirements. Another significant issue with the OFDM system is time synchronization, phase distortion, and time-varying channels. Another significant issue is the frequency offsets, which are brought on when the receiver's oscillator does not operate at the same frequency as the transmitter's oscillator. This offset causes a problem in the orthogonality of the sub-carriers whic, reducing the OFDM system’s performance high-speed mobile service causes synchronization error which leads to the loss of orthogonality at the receiver, this results in ICI. The ICI affects both channel estimation and detection of OFDM data symbols (Balachander and Krishnan 2021).

With the advent of new generations of wireless communication as well as the expansion of the Internet infrastructure, the need for more information rates is increasing day by day, and this need is double when we realize that newer technologies such, as the IoT are growing and developing. Therefore, the previous methods of using wireless internet will no longer meet this volume of information requests. Therefore, we have to find better ways. So far, different generations of wireless internet have come to work and the fifth generation will be used soon (Jouhari *et al.* 2019).

In all these generations, RF communication has been use. This means that a maximum bandwidth of up to 30 GHz has been propose. In addition, the transmitted data rate is implement up to several (less than 10 Gbps). It is easy to understand that even this rate of information will not be responsive. Consider a real example in this context (Gnewuch *et al.* 2018).

According to some reports in the fourth generation of wireless internet, the maximum data rate of 100 (Mbps) should be available to each user. According to some other reports, an average of 750 users connect to one connection point at a time. Therefore, each connection point should be able to deliver a 7.5 Gbps data rate, which is a very high data rate, and implementing such connection points based on RF radio bands would be very complicated, costly and complex. So you have to think of a solution to this problem (Strinati *et al.* 2019).

A relatively old method has been propose to solve the problem of bandwidth shortages, which is to migrate from lower central frequencies (such as RF waves) to higher main frequencies (such as light waves). Suppose that the bandwidth available in a telecommunication system is approximately 10% of the central frequency, so if we can build a telecommunication system that can operate at central frequencies of several hundred terahertz (visible light waves), It will give much more bandwidth than radio waves.

Optical telecommunications are introduce in the form of wireless and optical fiber. Optical telecommunications have been around since the 1980s and has expanded into fiber optics and wireless communications. Still, the spread of visible light wireless communications has grown much more in the last decade. Following the growth trend, we reach Li-Fi, this report aim to introduce and review Li-Fi networks.

Similar to every other communications scheme, the performance of the overall system can be improved by adapting channel coding. Several channel coding schemes have been investigated within OFDM systems, such as block codes, convolutional codes, and turbo codes. In this thesis, turbo codes are used to accomplish FEC. These codes can operate in the turbo cliff zone at close to Shannon's limit thanks to the combination of OFDM, turbo coding, and recursive decoding. For analysis of the OFDM system, first, we analyze the uncoded OFDM system and then apply convolutional code as FEC code and later Turbo code is used as FEC code. We compare and analyze the performance of uncoded OFDM systems with convolutional coded and Turbo coded OFDM systems.

Forward Modern digital wireless systems contain error control codes as a key component, allowing for dependable transmission over noisy channels. Turbo codes are largely regarded as the most potent error control code of practical significance over the past ten years. Turbo code was introduced in 1993 by Claude Berrou and his colleagues at ENST in France as a potent error control code (Joshi 2011, Bretagne 2008, Correia 2010). They gave it the name "turbo code" because the code's remarkable power efficiency was partially due to information being fed back from the decoder input to the decoder output, similar to how heat and pressure are fed back in a turbocharged car engine. Figure 1.1 displays the block diagram of the digital communication system.

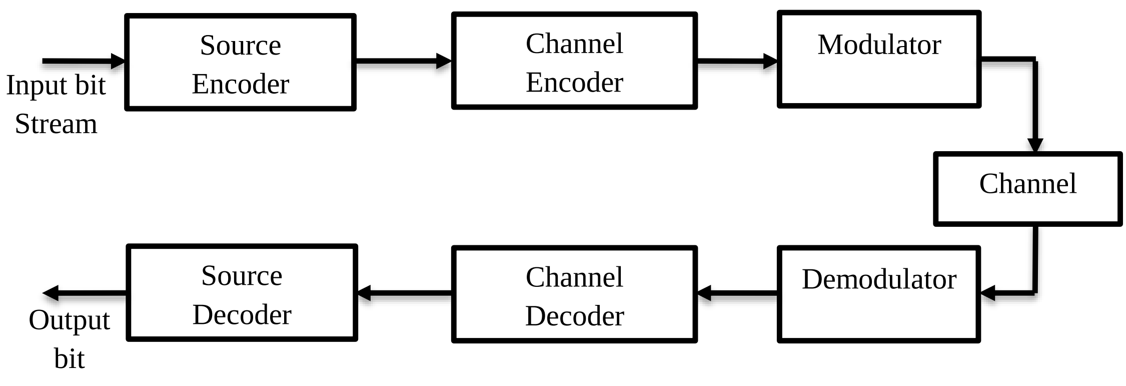

Figure 1.1 Block diagram of Digital Communication System

The source encoder converts information waveforms (text, audio, image, video, etc.) into bits, Based on the data bits it receives as input, the channel encoder adds code bits to the transmission bit stream. The channel decoder at the receiver uses these extra bits to correct issues that a noisy or fading channel causes into the transmission system. Due to the introduction of more bits into the transmission stream, the symbol rate through the channel must be increase to maintain the original rate of meaningful data bit transmission, increasing the signal's bandwidth need. Since bandwidth is expensive and frequency spectrum is typically closely restricted, bandwidth growth is frequently not an option in contemporary wireless networks. When the bandwidth is strictly constrained, the addition of an error-correcting code lowers the actual data rate. This flaw can be fixed by using higher-order modulation schemes, such as 8-PSK, 16-QAM, 64-QAM, etc., which we refer to as M-ary modulation schemes (Abdulhamid and Thairu 2019), instead of the typical wireless digital systems simple, reliable signaling schemes like BPSK, QPSK, and their derivatives.

1.1 Thesis Objective

An efficient method for high data rate transmission over multipath fading channels is an OFDM system. In this thesis, we analyze the performance of uncoded OFDM systems for different modulation schemes over AWGN and Rayleigh fading channels. We then apply FEC code and analyze the performance improvement of the OFDM system. We first apply conventional convolutional code as FEC and analyze and compare the performance of convolutional coded OFDM system with uncoded OFDM system. Later we develop a system model of turbo code and investigate its performance on AWGN and Rayleigh fading channels. We finally compare the performance of turbo-coded OFDM and convolutional-coded OFDM over uncoded OFDM under AWGN and Rayleigh fading channel.

1.2 Contribution of the Thesis

The main contribution of this thesis can be summarized in following steps:

1. Analyze and compare the performance of the OFDM system with different modulation schemes.
2. Analyze the influence of interference due to fading channels on an OFDM system.
3. Develop a system model of Turbo code and investigate its performance on AWGN and Rayleigh fading channels.
4. Compare the performance of turbo-coded OFDM and conventional convolutional coded OFDM over uncoded OFDM under AWGN and Rayleigh fading channel.

1.3 Thesis Organization

The introduction to the OFDM signals is presented in chapter one. The literature review is described in chapter two. The material and methodology are decribed in chapter three. The results and discussion is investigated in chapter four. Finally, with chapter five this thesis is finalized.

2 LITERATURE REVIEW

2.1 Background

OFDM is one of the most widely used modulation schemes in modern wireless systems. The efficiency of OFDM systems depends to a large extent on signal recognition and channel estimation methods (Vaigandla *et al.* 2021). For this reason, countless research efforts have been made to design effective methods for channel estimation and signal recognition. OFDM is a special implementation of MCM (Rahman 2021). Nearly 50% of the total bandwidth is saved by using the overlapping in MCM. However, it must gain orthogonality between subcarriers to achieve this strategy. The term "orthogonal" highlights the mathematical connection between the communication system's carrier frequencies. a modulation technique for transmitting digital data that makes use of several orthogonal carriers. Thus, the approach is a particular type of FDM in which the carrier is decreased between signals that are modulated on adjacent carriers by orthogonality i.e. the maximum of a carrier lies with its nearby carriers on a zero-crossing (Meshram and Rathkanthiwar 2013).

The useful data that needs to be delivered at a high data rate is first split up into several low-data-rate partial data streams. The modulated HF signals are introduced after each of these partial data streams has been individually modified using a traditional modulation technique, such as low bandwidth QAM (Adnan *et al.* 2021). The carriers must be orthogonal to one another in the function space for the receiver to be able to distinguish between the various signals while demodulating them. As a result, there is the least amount of interference between the partial stream of material.

The benefit of OFDM is that fine granulation makes it simple to tailor data transmission to the specifics of a transmission channel, like a radio channel, for instance. Carriers that are impacted by a narrowband interference that occurs inside the OFDM signal spectrum can be excluded from the data transmission. Therefore, only a small portion of the total data transfer rate exists (Lanante *et al.* 2020). However, when using a single carrier for broadband QAM, a narrow-band interference in the transmission channel may prevent a full data transmission. Destructive interferences brought on by multipath reception also only affect specific carriers.

MCM is the process of distributing data across several carriers (subcarriers). Contrary to the standard FDM system, which is typically set up to generate overlapping on the frequency axis, these subcarriers are orthogonal to one another, therefore there is no advantage to interference between them. The FFT algorithm makes it possible to detect subcarriers with high efficiency (Weinstein and Ebert 1971).

Symbol categorization is one of the current hot research topics in the OFDM system receiver. The Chameleon Optimization Algorithm will be used in this thesis to pick features, and we'll use those features to train and test the data using DNN. The NN built on LSTM will be trained for a single subcarrier.

Utilizing MIMO has significantly enhanced OFDM's performance in terms of channel capacity (Al-Gburi *et al.* 2022, Mahender *et al.* 2019). MIMO integration significantly increases the communication system's channel capacity over OFDM. However, because of the additional complexity the channel introduces, channel estimation, ICI cancellation, and PAPR reduction become challenging. With SDMA (Gamal *et al.* 2021), two users that are geographically apart can communicate using a single antenna. As more users access more antennas, SDMA becomes difficult. Signal detection for each user becomes crucial in this circumstance. Multi-user detection approaches are used to resolve this (Praveen Bagadi and Das 2013, Zaka *et al.* 2007, Khan and Das 2021).

Even though the OFDM system has a lot of benefits, one of the greatest issues affects how well and effectively it operates. Due to the implementation of IFFT, in time dominate in the OFDM signal is an amalgam of multiple sinusoids and produces a high PAPR. It makes the power amplifiers, which are located at the transmitter's front end, move in the saturation region. It led to aberrations that were nonlinear.

A MMSE estimator is an estimating strategy that reduces the MSE of the fitted values of a dependent variable, according to statistical and signal processing principles. To be more precise, the term "MMSE" in the Bayesian context refers to estimate a with a quadratic loss function. The posterior mean of the parameter to be evaluate is use as the MMSE estimator in this situation. The form of the MMSE estimator is frequently restricted to a limited class of functions since the posterior mean is difficult to compute. A common choice is the linear MMSE estimator, which is simple to use and to computes well as extremely adaptable. Many prominent estimators, such as the Wiener–Kolmogorov filter and the Kalman filter, were born because of this discovery.

Li-Fi and VLC concepts and theories are accurately present. In severely damaged situations, it is safe to utilize visible light for wireless connectivity, and it provides lighting. Li-Fi is a practical solution to wireless communication issues in terms of reducing network traffic. Increasing the wireless capacity of the IoT for 5G and beyond is made possible by turning lights into Li-Fi cells, which can be controlled by remote (Subha *et al.* 2020).

Analyzing over-determined systems, or systems with more equations than variables, may be done using the LS method, a common approach in regression analysis (a residual being: the difference between an observed value, For each equation independently, and the amount of fit offered by a model) (Charnes *et al.* 1976).

2.2 Visible Light Communication

It is a form of optical data transmission that operates in the range of 400 to 800 terahertz (780–375 nm). OWC systems include VLC as a subset.

Fluorescent lamps (ordinary lamps, not special communications devices) may transmit signals over short distances at ten kbit/s, or LEDs can do so at up to 500 Mbit/s, depending on the technology used. At maximum Ethernet speed (10 Mbit/s), the systems may transport data across distances as short as 0.6–1.2 kilometers (0.4–0.7 mi) (Kumar *et al.* 2012).

It's possible to employ VLC for ubiquitous computer communications because light-producing equipment (including indoor/outdoor lamps, TVs, traffic signs, commercial displays, and automobile headlights/taillights) are so widelissed (Obrien *et al.* 2008).

The digital data modulation technique known as OFDM divides a single data stream into several substreams for transmission over various channels in data communications and networking. FDM is a technique that OFDM uses to split the available bandwidth into a number of several with multiple frequency bands. OFDM was created in 1966 by Chang at Bell Labs, in 1971, Weinstein and Ebert improved it.

An FDM method developed by Bell Labs in 1966 is known as OFDM (Weinstein 2009, Chang 1966). Parallel data transmission is achieve by transmitting orthogonal subcarrier signals with overlapping spectra in close nearby. FFT techniques are the foundation of demodulation methods. When Weinstein and Ebert developed OFDM in 1971, they included the guard interval, which enhanced the orthogonality of transmission channels impacted by multipath propagation (Kumar 2019). Each subcarrier (signal) is modify using a typical modulation strategy (such as QAM or QPSK) at a low symbol rate. As long as you stay inside the same bandwidth, you'll get the same overall data speeds as you would with traditional single-carrier modulation (Weinstein 1971).

The fundamental advantage of OFDM over single-carrier systems is its capacity to deal with challenging channel conditions without the employment of complex equalization filters, such as the attenuation of HFs in a long copper wire, narrowband interference, and frequency-selective fading due to multipath. As opposed to a single rapidly modulated wideband signal, OFDM may be consider as employing numerous slow-modulated narrowband signals for channel equalization. It is possible to reduce ISI by using a guard interval between symbols because of the low symbol rate. Additionally, it is possible to boost the signal to no signal-to-noiseing echoes and time spreading (both of which are visible as blurring and ghosting on analog television). This approach also makes it simpler to create SFNs, in which multiple nearby transmitters simultaneously transmit the same signal at the same frequency. SFNs are possible because the signals from numerous distant transmitters may be constructively mixed (Kumar *et al.* 2012).

Researchers have investigated the Li-Fi access point architecture that makes use of OFDM. The state of Li-Fi technology is developing. Using OFDM theory, this technique can attain data rates as high as those that have been achieve in laboratories. To establish a safe and secure connection, information is communicate through the LED. Additionally, Li-Fi is predict to revolutionize the telecoms industry. These devices are power by the Li-Fi technology, which we can see. Li-Fi upgrades to the VLC standard will enable it to displace Wi-Fi in various locations and circumstances, making the world a better place (Subha *et al.* 2020).

An overview of Li-Fi modulation methods is provide in this article. Multiple users may communicate and light up simultaneously with Li-Fi's networked solution. LEDs are the sole light transmitters in Li-Fi, hence modified direct detection modulation methods are employ exclusively. Reaching a certain level of ferocity is within reach. It's easy to employ single carrier modulation techniques for low-frequency Li-Fi, but complicated computational unification processes are needed for frequency-selective channels *(Haas et al.* 2020).

An unguided beam of IR, visible, or UV light is used to transport a signal across long distances in OWC. Short-range communication is the most common usage of this technology.

The term "visual light communication" refers to OWC systems that operate in the visible spectrum (390–750 nm). LEDs used in VLC systems have the ability to pulse at very high rates without compromising the production of illumination or the human eye. VLC may be used in Wi-Fi local area networks, personal area networks, and automobile networks, to name a few. As an alternative, terrestrial point-to-point OWC systems, often referred to as FSO systems, use the near IR frequencies (750–1600 nm). The majority of these systems employ laser transmitters and provide a protocol-transparent link, a high data rate

(10 Gbit/sec per wavelength), and a potential backhaul bottleneck solution (Haas *et al.* 2020).

As an alternative, MCM methods offer an efficient solution for Li-Fi in terms of power, spectrum range, and computing workloads. Particularly in the case of Li-Fi, OFDM methods offer a feasible solution, as long as the DC wanders, adaptive bit and power loading approaches are address. Lighting needs must be check by Li-Fi modulation techniques as well as the technology itself. Avoid flickering and dimming control in variable modulation approaches. Has been a consideration (Haas *et al.* 2020).

For the purposes of Li-Fi communication, appropriate modulation schemes have been suggest. For flat frequency Li-Fi channels, single-carrier modulation schemes provide a straightforward option. Single carrier modulation methods can be use to achieve low to medium data speeds. The large data rates offered by MCM methods allow system performance to be tailor to the frequency response of the channel. A wide variety of optical OFDM modulation schemes have been presented in published research in order to fulfill specific illumination and/or communication objectives (Bahai *et al.* 2004).

Li-Fi, a novel and alternative wireless communication technology, has attracted significant attention. An increase in the usage of LEDs for indoor and outdoor lighting would benefit both commercial and academic sectors. Increased efforts have been made to integrate communication capabilities to standard lighting performance of LED bulbs in Li-Fi systems (Damerdash *et al.* 2021).

In order to execute the dual functions, the LED bulb and its power electronic drivers are subject to additional power losses and strains, as they are the same power source for illumination and communication. Because of this, correct LED lighting driver and control system design is essential. Li-Fi communication system designs are examine in this work, along with a systematic technique to evaluating energy efficiency and communication system performance criteria for Li-Fi systems developed as a result.

Mathematical models are use to examine various Li-Fi structures, communication modulators, communication modulation systems, and power converters. System designs, components, and communication modulators have a major impact on energy efficiency and system performance, according to simulation studies. A systematic technique to estimating energy efficiency and power losses for various components in Li-Fi systems has been present, and the findings collected so far support that claim. Adding communication capabilities reduces the predicted energy efficiency even further, making it less efficient than using regular light illumination alone. Modulation technique, modulator type, modulation index value, and forward lamp current all have a significant influence on the predicted energy efficiency (Damerdash *et al.* 2021).

Because of the employment of LEDs, Li-Fi is depend on VLC. The LEDs in this technology are modify so that they can transport data using light instead of electricity. Li-Fi technology is an excellent choice for data transmission for a number of reasons. Most significantly, data can only be transmit within the range of light. This means that hackers and spies cannot get their hands on the data, as it cannot be share outside of the United States. The rapidity with which data may be sent is another benefit of Li-Fi technology Figure 2.1 (Saadallah *et al.* 2021).

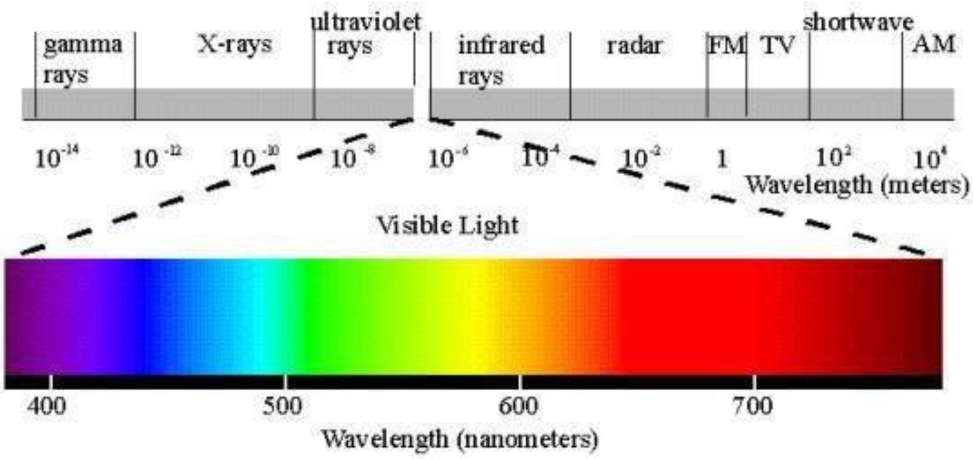

Figure 2.1 Wavelength spectrum location of VLC (Saadallah *et al.* 2021)

As wave shown, light waves have a 10,000-fold greater frequency than radio waves, making this technology possible. There are several methods to make greater use of Li-Fi, including directed illumination and energy efficiency, wall blocking, internal security, high data rate capabilities, and network capacity Integrated. This technology may be use in a variety of situations, including urban, educational, and medical settings as well as those where electromagnetic radiation are a problem. We have concluded that Li-Fi technology is a new technology that has been created to overcome many of the earlier difficulties that have been raised (Saadallah *et al.* 2021).

The optical equivalent of Wi-Fi, the Li-Fi technology is a rapid and low-cost wireless communication system. Because of the LED technology, this technology can transmit information that is invisible to the naked eye. When we talk about "vehicle data transmission," we are talking about a link between two cars that keeps everyone inside of them safe. Li-Fi technology is the most current technology created in recent years that requires a comprehensive examination of its long-term viability for commercial vehicles (Anbalagan *et al.* 2021).

In a transmission system, signals are send from one location to another. Electrical, optical, and radio signals are all examples of signals.

It is possible to magnify or re-shape the encoded message before re-transmission in some transmission systems, which include multipliers or regenerators.

It is one of the most often utilized Internet transmission methods. Transmission system also refers to the method used to move data between two locations. Everyday transmission methods include the internet, cellular phone networks, cordless telephones, etc.

Communication between vehicles is the most efficient method for reducing road accidents. The suggested application of this Li-Fi technology consists mostly of LED bulbs as the method of connectivity that operates by transmitting data across the light spectrum as an optical wireless channel for signal transmission. Since LEDs generate light, there is no longer a need for elaborate wireless networks or protocol. Accidents can be reduced to a higher extent due to the high-reliability communication between the vehicles thanks to the planned system (Anbalagan *et al.* 2021).

According to this study, the filtering and fidelity principles are use to design an ophthalmic-electro-decoder, which uses an optical-electro-decoder to decode optical signals. As an example, the Li-fi technology uses MATLAB Simulink to model the combination of Arduino boards, LEDs, and photo detectors, while the filter's operation relies on photonic band gaps in the structure, which are replicate by reflectance analysis using the PWE method. Optical filters and high Li-Fi work together to create an embedded program that can decode data and determine its meaning *(Swain et al.* 2019).

By fusing a 1-D photonic crystal structure with an Arduino development board, it was possible to construct and implement an opto-electro decoder using VLC. The aforementioned decoder is construct using both PWE simulation and Matlab Simulink with an Arduino interface. It can be utilize in a variety of embedded applications. Using Arduino's IDE and affordable hardware, it is possible to integrate photonic crystal structures with LEDs and photo detectors that are more advanced, resulting in a wide range of photonics applications (Sewaiwar *et al.* 2015).

It is hardware and software are design to be simple enough for even a non-technical person to utilize. An Arduino board can take inputs like a light sensor, a button, or even a tweet from Twitter and turn them into outputs like turning on a motor or an LED. If you are a creative person who wants to build interactive things or surroundings, the Arduino hardware and software are for you.

Your smart-phone or your TV may even be use as a remote control for your Arduino projects! The Arduino platform is popular among those who are just starting out with electronics, and for good reason. The Arduino does not require a separate piece of hardware (referred to as a "programmer") like earlier programmable circuit boards required in order to upload new code to the board. The Arduino IDE uses a condensed version of the C++ codebase, making learning to program with it easier. To wrap up, Arduino provides a uniform form factor that makes the micro-functionalities controllers more understandable.

A glass plane or plastic device in the optical path that is either bulk-dyed or has interference coatings is a common implementation of an optical filter since it selectively transmits light of different wavelengths. The optical properties of filters are fully described by their frequency response, which details how the filter affects each frequency component of an incoming signal (Madsen and Zhao 1999).

Most filters fall into one of two groups. Interference or dichroic filters are next, followed by the absorptive filter. It is possible to make some light sources translucent by using optical filters, which are typically made of transparent materials. Astronomers employ optical filters to limit the amount of light that reaches a particular region of interest, such as IR radiation, so that visible light does not interfere with the film or sensor and overwhelm the IR that is being study.

An optical filter blocks out all but a small portion of the visible light spectrum. It is common for them to be able to pass either broad or narrow bands of light, depending on the wavelengths that are being blocked (longpass vs. shortpass) (bandpass). Passband widths might be smaller or larger, and the change from maximum to minimal transmission can be abrupt or gradual. Filters with more sophisticated transmission characteristics, such as two peaks rather than a single band, are available (Nayak and Palai 2016). Filters with more regular properties are utilized in scientific and technical work and are more commonly seen in earlier designs used for photography (Major *et al.* 2015).

Full duplex bidirectional Li-Fi systems with many users can benefit from a new user allocation mechanism. Predefined frame structures for transmitting user data using RGB LED are use for the allocation of users to certain color groups. A color sensor that can tell apart colors is used to separate the users at the other end of the communication chain for primary user separation (Swain *et al.* 2019).

3 MATERIAL AND METHOD

3.1 Artificial Neural Network

The NN numerically represents the NNs in an individual's cerebrum, which are made up of a large number of linked neurons and nerve cells. The electrical signals produced by a layer of cells, or group of cells, are briefly motivated and used to create correspondences between neurons. This information is transmitted between neurons as electrochemical intersections known as neurotransmitters. These intersections are found on branches that connect them to the cell body, known as dendrites. Dendrites carry signals from a large number of neurons to the body of the nerve cell, where qualities are processed with the goal of choosing the neuron's outcome, whether or not to produce an electrical sign (also ref. A signal that is transmitted from one neuron to the next may have either an excitatory or an inhibitory effect on the receiving cell. While the excitatory influence makes the getting neuron fire, the inhibitory effect stops the neuron from terminating. Nevertheless, the influence of different information sources is constrained by the conductivity of the electrochemical junctions.

The three main parts of a neuron are dendrites, axons, and the cell body or soma, which are comparable to the branches, roots, and trunk of a tree. On its dendrite, or "tree branch," a neuron receives information from nearby cells. An modified version of a neuron's fundamental parts is shown in Figure 3.1.

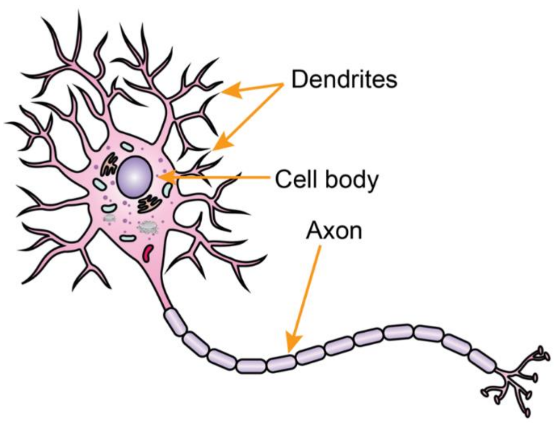

Figure 3.1 Neuron's basic components (Fernández-Montoya *et al.* 2018)

Utilizing mathematical concepts known as loads, ANNs modify the impact of contributions to the neuron. Each piece of information is replicated through the comparing weight before being sent to the neurons. In order to determine the outcome of the neuron, a neuron then sums up these weighted qualities notwithstanding the value of predisposition and transmits the outcomes via actuation work. Additionally, the bias values provide the neuron additional freedom to modify the output value. Hence the output of the neuron is always 0 whenever the inputs are 0. As a result, neurons can assess desired output based on the feature when bias value is present. Equation (3.1) displays the output of neuron.

$$z = \sum_i^n x_i \, w_i + b \tag{3.1}$$

x_i represents the contributions of that neuron, w_i is the weight value of each neuron to those contributions, b denotes the bias of the neurons, and z is the neuron's output. n represent the number of the inputs. The final output can be is calculated by Equation (3.2).

$$y = f(z) \tag{3.2}$$

where y is the final output and $f(z)$ is activation function. Figure 3.2 depicts the visual representation.

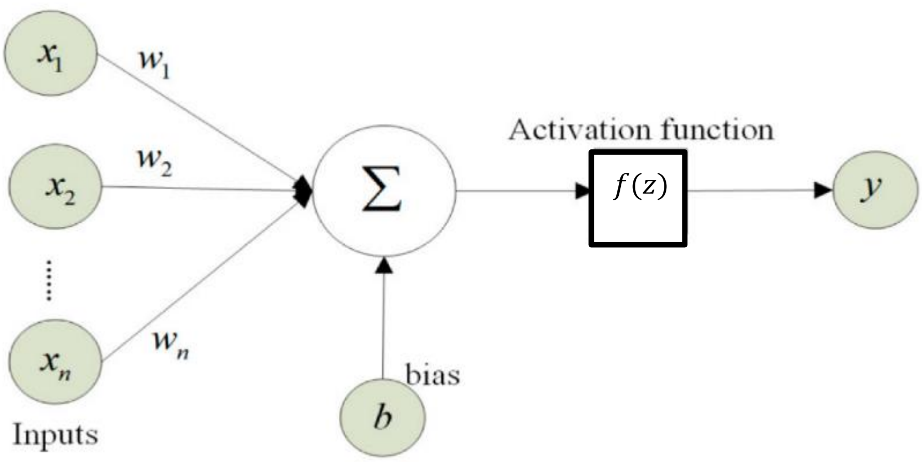

Figure 3.2 Visual representation of Neuron's Calculation operations (Esser *et al.* 2015)

In Figure 3.2, the x_1, x_2, and x_n are the inputs and w_1, w_2 and w_n are the related wheights values. n is the number of input, and $f(z)$ is the activation function. The neuron acquires the capability of setting nonlinear boundaries for independent direction by translating the results of the summation into an actuation effort. Further neuron identification in NN may also enable the creation of more baffling bounds for each class, enhancing the accuracy of predictions.

Three often utilized initiation capacities are the Hyperbolic Tangent, Sigmoid, and ReLU. In terms of execution, NNs with ReLU initiation capabilities have proven to be significantly better than those with other enactment capacities. Due to the non-linear nature of the calculations, the conclusion can be derived from the contributions by identifying the necessary components (Turčaník and Javurek 2016, Turčaník 2017, Abdoun *et al.* 2018, Karlik and Olgac 2011**,** Xu *et al.* 2015).

3.1.1 The feed forward neural networks

The neurons in an FFNN are distributed in layers, and the contributions made by neurons in earlier layers are correlated with the output of neurons in the layer above. The three different layer kinds in the network are yield, information, and secret. The basic layer to which contributions from the outside world are connected is the information layer. As a result, the quantity of execution needed to finish the task for which a NN is being used restricts the number of neurons in such layers. Additionally, in all circumstances, relying solely on information and result layers is insufficient to finish the work at hand because it restricts the variety and complexity of components that the NN can recognize in order to produce accurate forecasts. When working on the presentation of NNs, between the information and outcome levels, the majority of layers are added. Even if the number of neurons in the hidden layers is not limited by external variables, increasing the number of neurons in a hidden layer or storage layer makes the computations required to forecast a class of information more difficult and increases the time required for that prediction. The number of mixes that are visible in a hidden layer and trigger its neurons likewise increases as the number of neurons in that layer increases, in addition to the number of layers. For instance, the complexity of the element that could be found in deeper levels increases as the network's profundity increases. So-called profound NNs are networks with more than one stored away that can detect more mind-blowing highlights.

One of the key issues investigated with profound NNs is forecasts are largely confined to these elements due to the overfitting feature. Therefore, it is possible that any further data sources that could belong to that class but do not activate the neurons connected to such elements will be misclassified. To solve this issue, a set number of hidden layer neurons are randomly eliminated after each preparation stage cycle. This forces the NN to come up with new methods for making decreases its reliance on explicit elements while maintaining the same forecast. This tactic, called Dropout, significantly enhanced NN forecasts.

The predictions made by a NN are the outcome of calculations made in each neuron. This update is finished by estimating the difference between necessary and anticipated quality, often known as expenditure, using the SSE method illustrated in Equation (3.3).

$$C = \sum_i \frac{1}{2} (y_i - \hat{y}_i)^2 \tag{3.3}$$

where C, is the distinction between required and desired quality, and y_i is the expected value of the ith layer, while $\hat{y}_i$ is the actual mandatory incentive for the i yields in the i^{th} layer (Kingma and Ba 2014).

By back-spreading over NN and updating the predispositions' and loads' in light of slope drop computation, slope-based attributes, the predispositions and loads are refreshed. This calculation takes into account the determined error in the preceding layer for each weight and propensity (Glorot and Bengio 2010).

In older and earlier NNs, such contributions to a NN were managed by converting source layers to output layers. This adjustment causes highlights in one of the aspects to be extended based on how big that aspect is, which leaves the two-layered information with a data gap.

In order to address this problem, two-layered data sources are searched for highlights using NNs, making it possible to find neighborhood highlights regardless of the orientation of such features in the data (Krizhevsky *et al.* 2017).

NNs are utilized to reproduce the inferotemporal way in the human visual system. These networks identify highlights. Since the channels are two-layered, so are the identified elements.

With this method, the state of the input is unaffected while the highlights of the 2-layered contribution can be separated (Shin *et al.* 2016).

Channels are equipped to identify various highlights depending on the information sources and the assignment requested by the NN. The clusterscalculated using the stated procedures for layer comparison, and another exhibit is built (Szegedy *et al.* 2016).

Another significant type of layer in NNs is the pooling layer, which may be further separated into max-pooling and normal pooling layers. Two-layered channels in max-pooling layers become tangled as a result of the layer's contribution. However, utilizing max-pooling layers, a new cluster is created after the channels that contains the most severe features discovered in each maximum pooling channel.

The neurons in the completely linked layers are now able to discern sophisticated two-layered neighborhood highlights in the data due to the various channel mixtures in the layers. A number of channel layouts are then created for each layer by the NN, with more advanced levels being able to blend highlights from many layers (Konda 2016).

3.1.2 Training of the ANN

In tasks where distinct choices are made using varying load values among their neurons, two indistinguishable NNs could be used. The magnitude of the load between two neurons establishes the type of effect, the degree to which the previous layer's neuron has an impact on the subsequent layer's neuron, and the relevance of that influence (Sethi and Jain 2014).

Backpropagation plays a crucial role in the widespread usage of NNs because, when used to update the value of the network's loads, it significantly improves the network's display. Equation (3.4) demonstrates that in order to refresh the loads w of an ANN, the back-propagation needs three characteristics: the rate at which the network's results advance (Hecht-Nielsen 1992).

$$\widehat{w} = w - EL\frac{\partial F}{\partial w} \qquad (3.4)$$

In Equation (3.4), the $\widehat{w}$ is the estimated of the weighted value, E is the error, L is learning rate, and the $\frac{\partial F}{\partial w}$ is the derivative of the output of activation fucntion over weight variable. This control of delta values guarantees that detonating weight values are avoided, allowing the loading values that lead to the fundamental error to be recognized (Miikkulainen *et al.* 2019).

Three potential characteristics may be formed by determining the rate of development of result blunder with regard to weight values, namely:

1. A demonstration of a positive worth, showing that a person's error increases as their weight self-esteem rises. The weight esteem must be decreased in this manner by the work out delta esteem in order to lessen the disparity between the NN and the essential results.

2. A negative value, which shows that the mistake has been reduced as a result of increasing the weight's value. The existing weight value must be increased by the selected delta value in order to lower the error worth and get extremely accurate results.

3. A value of 0, which indicates that the existing weight value is adequate.

Based on these prospective qualities, the upsides of the loads in NN might be updated. This would help to bridge the gap between what the NN expects and what is actually needed to finish the ANN's task. The optimal NN exhibition, which has been established by determining optimal load values by lowering error by refreshing load values (Schmidhuber 2015).

3.1.3 Transfer learning

The NN preparation depends on the mismatch between the qualities the NN produces based on its current predispositions and loads and the results needed to provide this information. However, those limits cannot be swiftly updated in an effort to avoid missing the slightest disaster on a global scale. Additionally, adjustments to the borders of layers that are closer to the information layer are not relevant because updates start from the yield layer and propagate upward, or backward, to the information layer. Because of this, creating meaningful NN requires significant resources and testing in order to complete the essential presentations (Torrey and Shavlik 2010, Tan *et al.* 2018).

The identification of the rough highlights, which are most likely to be divided amongst various applications that NNs are employed for, is the responsibility of layers that are closer to the information layer. Channels in the layer that is closest to the information layer, for instance, could recognize the comparison features, such as upward, level, and inclining lines, in the scenario where a CNN is needed for recognizing facial highlights or distinctive mark inclusions. By adding those components in a subsequent layer, complex high-lights that are more involved with completing important tasks are characterized. In any case, during preparation, layers that are closer to the result layer receive more frequent refreshes. Because of this, the preparation process can be significantly sped up by beginning with the recently noticed crude high-lights (Ravishankar *et al.* 2016, Yin *et al.* 2019).

Loads and inclinations are not randomly assigned in move learning, nor does NN preparation start with no preparations. Additionally, NN construction, defined by the quantity of elements that must be recognized at each level of complexity and the complexity of the elements that must be recognized in order to achieve desired results, may vary, starting with one application then moving on to the next. This is true for both the number of elements that must be recognized at each level of complexity and the complexity of the elements that must be recognized in order to achieve desired results. Then, whether or not the NN is ready for comparative application rather than indistinguishable application, it may be deployed for preparation.

Preparation makes advantage of crude highlights that NN had no doubt seen, and it also ensures that used buildings are appropriate for the applications. As a result, move learning had enabled a crucial reduction in preparation time while still delivering the necessary presentations (Gopalakrishnan *et al.* 2017,Yu *et al.* 2017).

4 SIMULATION RESULTS

4.1 Introduction

In this thesis, the DL Toolbox's LSTM network is used at the receiver for signal detection in OFDM systems for symbol categorization. The LSTM-based NN is trained for a single subcarrier, and then the SER is calculated and compared with the LS and MMSE estimates. The offline training and online deployment phases of this initial trial are expected to see a fixed wireless channel. Each transmitted OFDM packet has a random phase shift performed in order to assess the NN's stability. We take into account the effects of the CP length and the number of pilot symbols.

For all methods of channel estimation, the blockdiagram of an OFDM system is essentially the same. As a result, both the DL model and the traditional LS estimation are used in this study; the only variation is in how the estimation is carried out in each technique. The basic building components of an OFDM system are shown in the following OFDM block diagram see Figure 4.1.

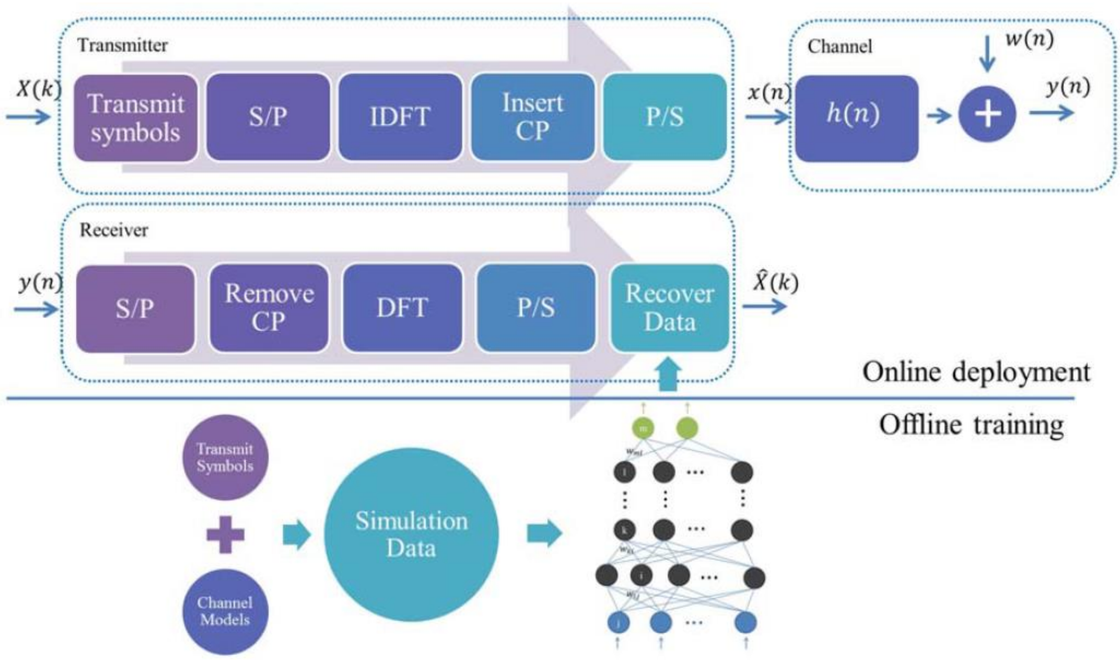

Figure 4.1 the blockdiagram of OFDM system

On the transmitter side, the broadcast stream is first changed from a serial to a parallel stream (S/P). QPSK is the way that this system changes the signal. After the IDFT transforms the signal convert from the frequency domain to the time domain, and a CP is added to it. The length of the CP shouldn't be longer than the channel's maximum delay spread in order to reduce ISI. The channel can now be utilized to send the data. A multipath channel with two taps comes to mind. The SNR value indicates that the channel mostly introduces complex noise with a known variance. The received signal $y(n)$ can now be represented as,

$$y(n) = x(n) \otimes h(n) + w(n) \tag{4.1}$$

where *x(n)*, $h(n)$, w(n), and sign $\otimes$ are input signal, channel, AWGN signal, and circular convolution, respectively.

The CP is eliminated at the receiver, where it is then converted back into frequency domain. Finally, utilizing the frequency domain signal that was received is parallel to serial conversion. must be transformed from the bit groups into a serial stream of bits.

$$Y(k) = X(k)H(k) + W(k) \tag{4.2}$$

where the DFT of *y(n), x(n), h(n),* and *w(n)* are $Y(k)$, $X(k)$, $H(k)$, and $W(k)$, respectively.

4.2 Model Training

The models are trained by treating the wireless channels and OFDM modulation as if they were black boxes. In the past, academics have created a variety of channel models that, in terms of channel statistics, accurately describe the real channels. The training data for these channel models can be obtained through simulation. Each simulation starts with a random data sequence as the transmitted symbols, followed by a sequence of pilot symbols that must be fixed during the training and deployment phases to make the correct

OFDM frame. The channel models are used to simulate the current random channel. The OFDM signal is made from OFDM frames that have been changed by the current channel distortion and noise. The training data comes from both the signal that was sent out and the signal that was received. The DL model gets its information from the pilot block and one data block that were sent. The model is tweaked to reduce the difference between what the NN comes up with and what is sent. There are various methods to represent the difference. The L loss is the setting we use in our experiment.

$$L = \frac{1}{N}\sum_k \left(\hat{X}(k) - X(k)\right)^2 \tag{4.3}$$

where the symbols that transmitted in this scenario are $X(k)$, which represents the supervision message, $\hat{X}(k)$ represents the prediction, and N is the symbol number.

We use a DNN model with five layers. Three of those layers are hidden. There are 256, 500, 250, 120, and 16 neurons in each layer, in that order. The number you put in is equal to the sum of the real and imaginary parts of the two OFDM blocks that hold the symbols and pilots that are sent. A single model that was trained on its own is used to group and predict each of the 16 bits of data that are sent. The output is then made by stringing together the predictions. Most layers use the Relu function as the activation function, except for the last layer, where the Sigmoid function is used to translate the output to the range [0, 1].

We have conducted a number of experiments to demonstrate the efficacy of DL algorithms for simultaneous channel estimation and symbol identification in OFDM wireless communication systems. The BERs of a DNN model under different SNRs are compared with those of conventional methods after it is trained using simulation data from SNRs. In the tests that follow, it is shown that the DL-based approach is more resistant to nonlinear clipping noise, fewer training pilots, or the absence of the CP than LS and MMSE. In our tests, a 16-length CP and an OFDM system with 64 sub-carriers are taken into consideration. The wireless channel uses standard urban channels with a maximum delay of 16 sampling periods and is based on the wireless world initiative, where the carrier frequency is 2.6 GHz and there are 24 routes. It uses QPSK as the modulation technique.

4.3 Least Square Channel Estimation

A few variations are taken into account when comparing the current OFDM system to channel estimation. The number of pilots that are added into the transmitted symbols after the bits have been modulated indicates how many subcarriers are already known on both sides. The IDFT is carried out on each block after the symbols have been organized into blocks, and CP is added, before the blocks are put into the modulator and transmitted. After the CP is eliminated at the receiver, each received OFDM symbol is subjected to DFT, and the signal is then carried out. Because the sent signal comprises pilots at certain pilot carriers whose locations in the frequency domain are known, the receiver can figure out how the wireless channel will affect data subcarriers and learn more about the wireless channel at the pilot carriers. By adding up the channel values between the pilot carriers, the receiver can figure out what the channel is in the data carriers. But it needs to know the channel in the data carriers to do this. Interpolation technique is then used once the pilot symbols have been dispersed throughout the OFDM block utilizing structures like comb-type pilots. Interpolation is employed to determine the channel impulse response from the overall data subcarrier structure. After interpolation, all OFDM symbols contain data on the channel response. The fading effect and/or cochannel interference are then eliminated, and the original broadcast signal is restored, using this information as input to equalizers. The data carriers are then extracted from the equalized symbol. The pilot carriers can be omitted because they don't offer any information. To convert the information back into a bit stream, the incoming signal will be demodulated (Wu *et al.* 2020). The number of bits that were appropriately sent after transmission or that were successfully detected at reception after going over the channel will be determined by comparing the sent and received bits. The BER, or bit error rate, is a measurement of the proportion of error bits—i.e., bits with errors—to all the bits transmitted over a predetermined period of time as signals are conveyed across a channel, is used to achieve this.

4.4 Deep Learning Model

The primary tasks of the model in an OFDM system are signal detection and channel estimation. It uses a single NN to carry out channel estimation and signal identification simultaneously rather than two separate NNs for each task (Abdulhamid and Thairu 2019).

4.4.1 Data

The actual data that will be supplied to the model is produced using a sizable dataset of channel replies. The train, validation, and test datasets are separated into three sets, with a ratio of 6:2:2, from the channel response dataset. In this scenario, training data are obtained by simulating the real dataset that will be used to train the model. In each simulation, the sent symbols and various channel responses are first created using a random data sequence.

Input and Output of the Model As was previously stated, an OFDM system is used to simulate the signals that are transmitted and received. The transmitted and received signals make up the model's input, with the transmitted signals serving as the model's target data and the received signals serving as its input. The original transmitted data should be the output of the model because signal detection has been implemented, which should allow for the recovery of the original signal before transmission.

4.5 Model Structure

The input layer, three hidden levels, and the output layer make up the model's five layers. Each layer is made up of neurons; there are 256, 500, 250, 120, and 16 neurons in each layer, respectively (Abdulhamid and Thairu 2019). Each of the five layers is dense and deeply connected, which means that all of the neurons in one layer are connected to all of the neurons in the layer above it, creating a fully integrated network (Clark 2006). Due to its frequent ability to produce higher performance, the Relu function is used as the activation function for hidden layers in NN models (Wang *et al.* 2020). However, the Sigmoid function is used for the output layer's last layer (Abdulhamid and Thairu 2019). The DNN model employs a frame of 128 by 1 of incoming data, which is made up of one pilot block of 64 by 1 and one data block of 64 by 1, as input. As a result, the 256 input layer neurons are equivalent to both the real and imaginary sections of the two OFDM blocks. After each set of 16 bits from the transmitted data is predicted using a separate model, eight unique but related networks are built, each of which has the same input and structure and is in charge of detecting 16 bits. The output is composed of 16 neurons. The initial 1-16 bits must be detected by the first network, followed by the 1-17-32 bits by the second.

In an OFDM system, the model is trained to make the difference between what the NN gives out and what is sent as small as possible. This is done so that the channel can be estimated and the signal can be identified. The DNN model makes the output that gets the data back without directly figuring out what the wireless channel will be. The received data is used as input to retrieve the whole chain of sending data.

4.6 Compile the Model

The model is set up for training during the compilation stage. In our illustration, the degree to which an recognized value deviates from its true value is determined by the MSE between labels and predictions MSE loss function (Li *et al.* 2019). The Adam is an adaptive moment estimation optimizer is used for optimization because it performs effectively for problems with lots of data. The optimizer receives information from the loss function about its direction of travel. The weights and learning rate of the DL model are modified using optimizer classes or methods in order to reduce losses. The model is implemented using a metric function that calculates the BER, whereas the metric can be any loss function (Meena and Lal 2018). Metrics are a type of function that are used to assess how well a model is working.

4.7 Fit the Model

The next stage in ML is training, which is crucial. In order to reduce the loss function, model training aims to fit an ML algorithm with the best weights and bias. Utilizing the train and validation data, A specified number of epochs are used in the fit function's model training. The batch size, number of epochs, goal data, and a number of other important factors must all be specified at this point. In this study, the broadcast signals serve as the model's target data while the received signals serve as its input data. Generators serve as the study's data source, which produce batches, hence the batch size is not given (Meena and Lal 2018).

4.8 Evaluate the Model

The assessment process, which is the last phase, gauges the model's performance using test data that is brand-new to the model and is measured against the loss value. In the test stage, the model's loss value and metrics values are returned by the evaluate function using the test dataset.

4.9 Simulation Results

We'll talk about the outcomes of the simulation for the LS channel estimation, signal detection, and analysis of the DL model's channel detection, and assessment. After channel estimation, both strategies use QPSK digital modulation by eight pilots to calculate the average BERs at varying SNR values. The Reference list contains the codes that were used to produce the simulation results.

4.9.1 Least square channel estimation

Simulation of the bits in the OFDM system and detection are used to get results. The channel response, and the SNR value are all used by the OFDM system in this process. A considerable number of received signals can only be generated by the simulation if there are numerous channel responses and bit sequences. Since a large number of BERs were gathered, the calculating of average BER was necessary as an output. The graph illustrates the performance of the LS channel estimation technique for SNR values ranging from 0 to 25 dB. The system performs better as the value of BER lowers, indicating that the increase in SNR is what causes the change in BER. As demonstrated in Figure 4.2, the BER curve saturates at SNR levels higher than 15 dB, that was the highest value attained and precluded further improvement. Because no prior channel data were used in the detection, the all LS performance does not look to be precise enough.

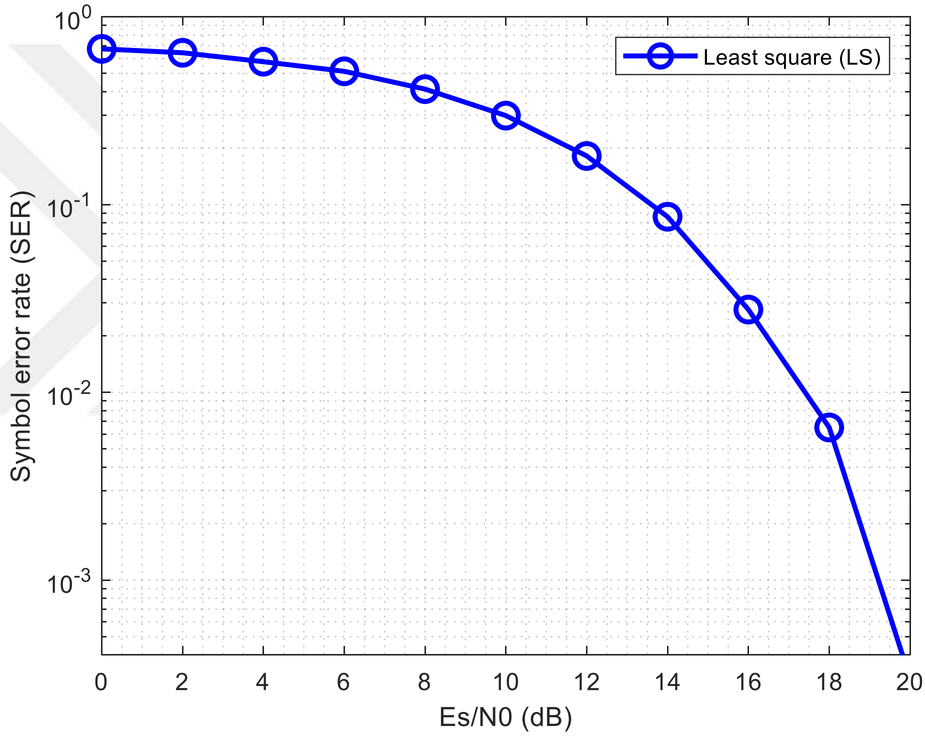

Figure 4.2 the curve of BER from LS method

In Figure 4.2, the x axis represent the SNR and is shown in Equation (4.4).

$$SNR = \frac{E_s}{N_0} \quad (4.4)$$

where E_s is energy of the signal, and N_0 is the noise spectral density.

4.9.2 Deep learning channel estimation

The model is evaluated after training to produce results. By using the received signals as input to predict the initially transmitted signals, evaluation demonstrates how supposed model do in terms of BERs. The DNN model's channel estimation outcomes are achieved, and Figure 4.3 also demonstrates that raising the SNR results in a small BER value and, thus, higher system performance. The training data produced by the model can be used to learn the properties of the wireless channels. The DL curve's performance steadily increases as BERs drop, unlike the LS, which reaches saturation at 15dB. The best performance is provided by SNR values of 25db. In reality, since the impact of the channeles are stronger than the impact osthe noise in this SNR range, the DNN is better able to learn the channel when training is done at a high SNR value. This suggests that the DNN model could estimate the channel in the presence of additional noise.

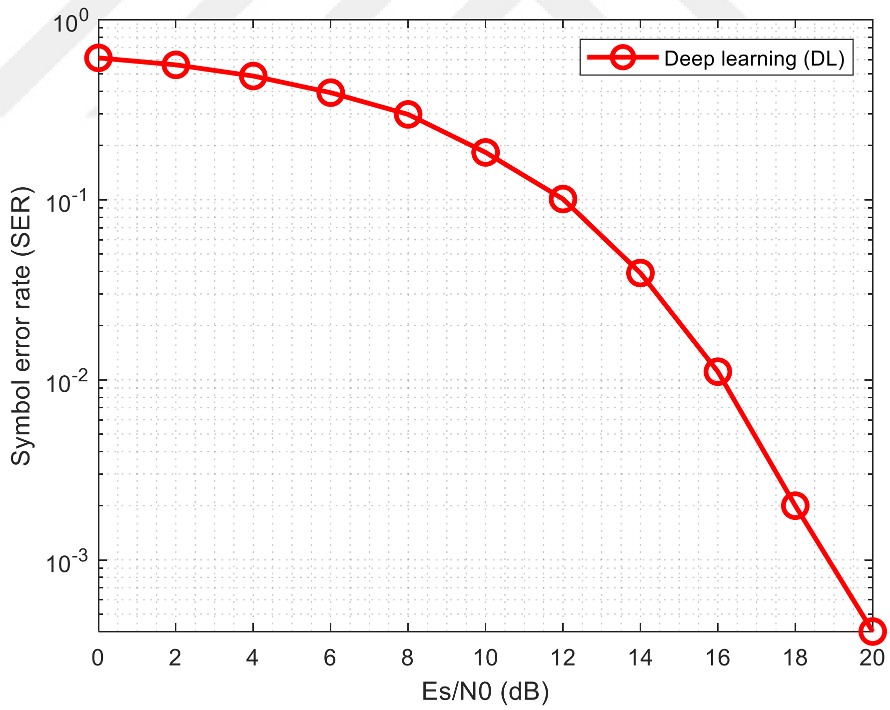

Figure 4.3 BER curve for DNN model

The BER curve for MMSE model result is shown in Figure 4.4.

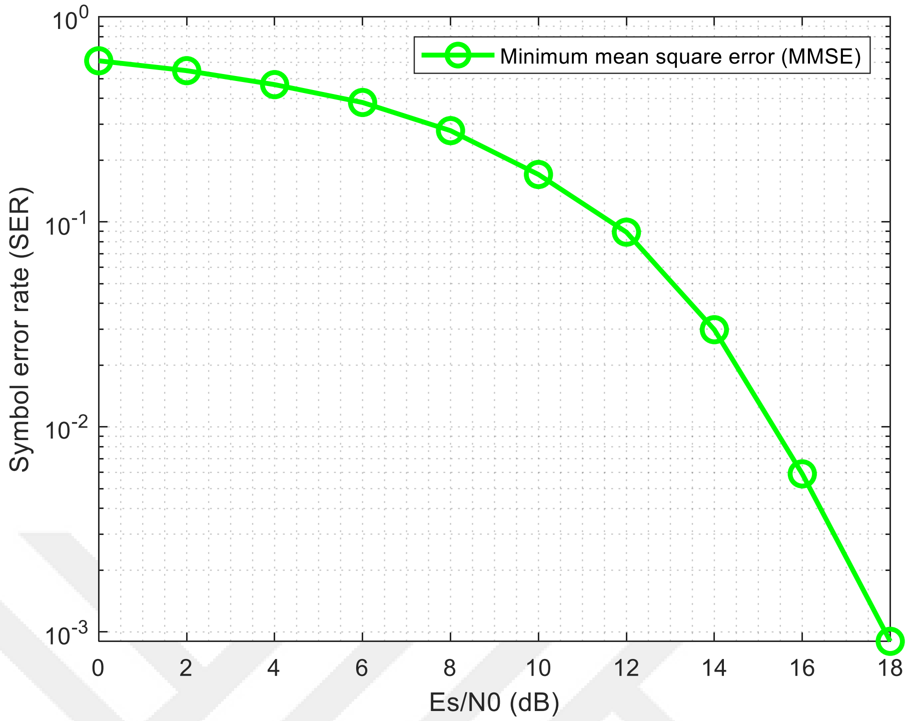

Figure 4.4 BER curve for MMSE model

4.9.3 The comparing of LS, MMSE method via deep learning method

In this study, the simulation compares the effectiveness of channel estimation using the DL approach versus channel estimation using the classic method LS. When BERs are compared at various SNR levels, it can be shown that both approaches demonstrate how channel estimation can raise BER values as SNR rises. Since the LS method does not rely on prior knowledge of the channel's properties, it performs worse than the DL model when the DL performs far better than the LS since it gains this knowledge through training. In contrast to the LS approach, after 15dB, the DL technique can still decrease its BER with rising SNR. The comparision is shown in Figure 4.5.

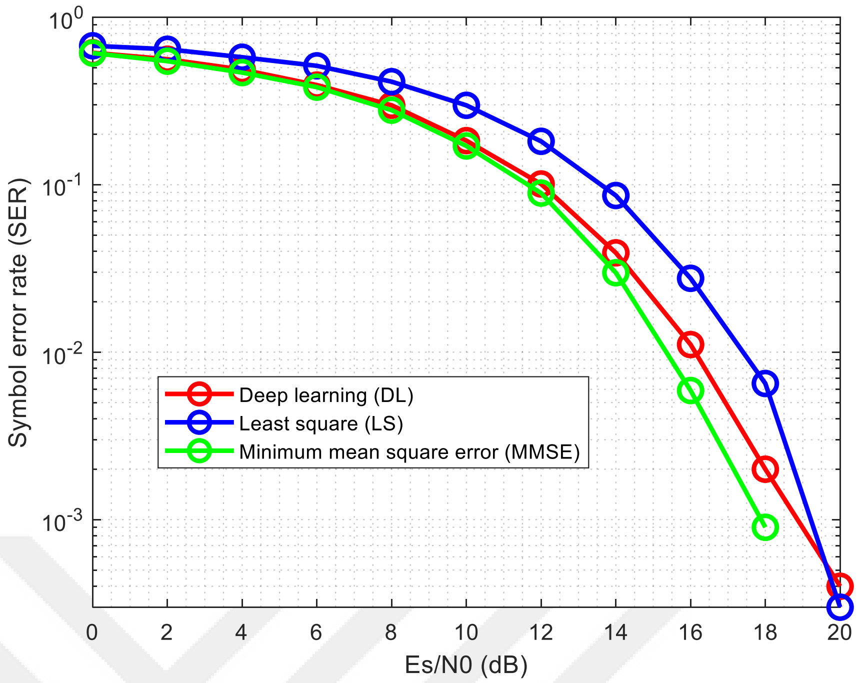

Figure 4.5 the comparision between DL and LS method for BER curves

The channels in the simulation's online deployment phase are created using the identical statistics as those in the offline training phase. However, there could be inconsistencies between the two stages in real-world implementations. It is crucial that the trained models be quite resilient to these discrepancies. This simulation examines the effects of variations in the channel model statistics used throughout the training and deployment phases. When the maximum delay and the number of paths in the test stage differ from the values used in the training stage discussed at the beginning of this section, the BER curves are shown in Figure 4.5. According to the graphic, changes in channel model statistics have little to no impact on how well symbols are detected.

5 CONCLUSION AND FUTURE WORKS

5.1 Conclusion

Multipath fading and ISI can be addressed with OFDM, a good MCM technology. The data stream that needs to be broadcast is split up into numerous lower rate data streams in this modulation technique, each of which is modulated on a separate subcarrier. By adding a brief pause known as the guard time interval to OFDM signals, ISI is eliminated. The duration of the guard time interval is chosen to exceed the channel delay spread in order to counteract multipath fading and almost eliminate ISI. Increased need for higher bit rates is being driven by a rising number of emerging technologies such as the IoT and 3D meidas as well as the development of new wireless communication generational generations. Therefore, the previous methods of using wireless technology need to be improved and enhanced. In this thesis the DL Toolbox's LSTM network used to achieve symbol classification at the receiver for OFDM systems' signal detection. The SER is determined and compared with the LS and MMSE estimations after the LSTM-based NN has been trained for a single subcarrier. In this initial experiment, it is expected that the wireless channel will be fixed during the offline training and online deployment phases. Each transmitted OFDM packet has a random phase shift performed in order to assess the NN's stability. We take into account the effects of the CP length and the number of pilot symbols. Results show that DNNs perform better than LS estimates and is able to recall and analyze the complex properties of wireless channels. Overall, BER decreased as SNR rose, however the LS curve technique reaches saturation at SNR levels beyond 15 dB. The DL strategy is shown to be more robust than LS in a scenario where 8 pilots are taken into consideration, even though the DL-based method still has the capacity to minimize its BER with increasing SNR. We employed a method for DL-based channel estimation and signal identification in OFDM in this thesis. The DNN model that recovers the original sent data after transmission through an OFDM was taken into consideration. The BER of the simulation results and channel estimation using the LS approach are then compared.

5.2 Future Works

For future works the author recomment the metaheuristic optimization method such as Ant colony optimization and particle swarm optimization to select the best feature of the signals and use these feature to DL for signal detection in the VLC.

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