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ISTANBUL AYDIN UNIVERSITY

INSTITUTE OF GRADUATE STUDIES

CHANNEL ESTIMATION USING DEEP LEARNING FOR 5G COMMUNICATION SYSTEMS

MASTER'S THESIS

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Department of Electrical and Electronics Engineering
Electrical and Electronics Engineering Program

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DECLARATION

I hereby declare that all information in this thesis document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this thesis.

Hamouda M. H. M. Hussain

FOREWORD

I would like to give my sincere appreciation and thank my supervisor Assist. Prof. Dr. NECIP GÖKHAN KASAPOĞLU for the opportunity of developing this thesis throughout my last year of Masters Course. It has been truly a pleasure to work under his supervision with the continuous series of effective, righteous and straight to the point advices.
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At last, but most important, I present my special gratitude/appreciation to all my family, especially to my parents for all the dedication and hard work which made my academic journey possible, to my brothers, sisters, nephews and nieces for all their support, understanding and motivation throughout these two years.
Finally, I would love to send a special thanks to my sister NAJAT who have given me all kind of supports financially, emotionally and scarified a lot of her resources for my own sake to make sure that I finishes my masters course from A to Z without any troubles.

April 2021 **Hamouda M. H. M. Hussain**

TABLE OF CONTENTS

Page

ABBREVIATIONS

UL	: Uplink
DL	: Downlink
UE	: User Equipment
LOS	: Line-of-Sight
BER	: Bit Error Rate
SER	: Symbol error rate
SNR	: Signal to Noise Ratio
ICI	: Inter-Channel Interference
AWGN	: Additive White Gaussian Noise
1G	: First Generation of mobile communications
2G	: Second Generation of mobile communications
3G	: Third Generation of mobile communications
4G	: Fourth Generation of mobile communications
5G	: Fifth Generation of mobile communications
3GPP	: Third Generation Partnership Project
CP	: Cyclic Prefix
MIMO	: Multiple-Input Multiple-Output
OFDM	: Orthogonal Frequency Division Multiplexing
QPSK	: Quadrature Phase Shift Keying (2 bits per symbol)
16 QAM	: Quadrature Amplitude Modulation (4 bits per symbol)
32 QAM	: Quadrature Amplitude Modulation (5 bits per symbol)
64 QAM	: Quadrature Amplitude Modulation (6 bits per symbol)
256 QAM	: Quadrature Amplitude Modulation (8 bits per symbol)
IDFT	: Inverse Discrete Fourier Transform
DFT	: Discrete Fourier Transform
LS	: Least square
MMSE	: Minimum Mean Square Error
CSI	: Channel State Information
i.i.d	: Independent and Identically Distribute
STBC	: Space-time block
OSTBC	: Orthogonal Space-time block
CNN	: Convolutional Neural Network
DNN	: Deep Neural Network Generative Adversarial Networks
GANs	: Generative Adversarial Networks
AEs	: Autoencoders
PARP	: Peak to Average Power Ratio

LIST OF FIGURES

Page

LIST OF TABLES

CHANNEL ESTIMATION USING DEEP LEARNING FOR 5G COMMUNICATION SYSTEMS

ABSTRACT

Users' starvation for more reliability, high speed and capacity wireless communication have caused the invention of 5G NR communication system. As we know the recent communication technologies are designed on the basis of conventional communication philosophies, which significantly limit additional performance perfections and that is the root of daunting limitations. one of the important areas of the mobile communication is the wireless channel estimation method which can significantly improve the performance of the whole system, and particularly for 4G-systems and 5G-systems.

In this thesis we examine the baseline channel estimation methods used for orthogonal frequency division multiplexing (OFDM) systems, such as the minimum mean square error 'MMSE' estimator and the least square (LS) estimator. We studied the MMSE and LS estimators' architecture an examine their performances. And prove that the MMSE estimator performance is better but it is computational complexity is high, in contrary the LS estimator has low complexity with low performance.

Therefore, in this thesis we propose a different and efficient solution for channel estimation which is based on machine learning techniques and in particular we used deep learning techniques to overcome the performance issues associated with the traditional channel estimation baseline methods, we assess the proposed estimator performance on basis of Long Short-Term Memory (LSTM) and symbol error rate for 16 QAM systems for a multi-user communication system. We also evaluate estimator computational accuracy and feasibility.

Keywords: *5G Communication Systems, Channel Estimation, OFDM, LS Estimator, MMSE Estimator, DNN, LSTM, Complexity calculation.*

5G HABERLEŞME SISTEMLERI IÇIN DERIN ÖĞRENMEYI KULLANARAK KANAL KESTIRIMI

ÖZET

Kullanıcıların daha fazla güvenilirlik, yüksek hız ve kapasiteli kablosuz iletişim ihtiyacı, 5G NR iletişim sistemlerinin geliştirilmesine neden olmuştur. Bilindiği gibi, son iletişim teknolojileri, sınırlı performanslı geleneksel iletişim felsefeleri temelinde tasarlanmıştır. Kanal kestirimi mobil iletişimin önemli alanlarından biri olup, özellikle 4G sistemleri ve 5G sistemleri için tüm sistemin performansını önemli ölçüde artırabilen bir yöntemidir.

Bu tezde, minimum ortalama kare hatası (MMSE) kestiricisi ve en küçük kare (LS) tahmincisi gibi ortogonal frekans bölmeli çoğullama (OFDM) sistemleri için Temel kanal tahmin yöntemleri incelenmektedir. MMSE ve LS tahmin edicilerinin çalışma prensipleri ve performansları incelenmektedir. MMSE tahmincisinin performansının daha iyi olduğunu ancak hesaplama karmaşıklığının yüksek olduğunu, LS tahmincisinin aksine düşük karmaşıklığa fakat düşük performansa sahip olduğu görülmektedir.

Bu nedenle, bu tezde, makine öğrenme tekniklerine dayanan ve özellikle geleneksel kanal tahmin yöntemleriyle ilişkili performans sorunlarının üstesinden gelmek için derin öğrenme tekniklerini kullandığımız kanal kestirimi için farklı ve verimli bir çözüm önerilmiştir. Önerilen kestirimci performansı, uzun kısa süreli bellek (LSTM) temelli ve çok kullanıcılı 16 QAM bir iletişim sistemi için sembol hata oranı uyarınca tahmin edicinin hesaplama doğruluğu ve performansıyla değerlendirilmektedir.

Anahtar Kelimeler: *5G İletişim Sistemleri, Kanal Tahminleme, OFDM, LS Tahmincisi, MMSE Tahmincisi, DNN, LSTM, Karmaşıklık hesaplaması.*

1. INTRODUCTION TO COMMUNICATION SYSTEMS

1.1 Communication System Block Diagram:

For overall argument of communication system, the following figure (1.1) illustrates a widely used block diagram. Both data and voice transmission systems inevitably include three main subsystems, irrespective of the individual application theses subsystems are: *(Tx)*-transmitter, (*Rx*)-receiver and channel (Rodger E & William H, 2015; YRKI, 2016).

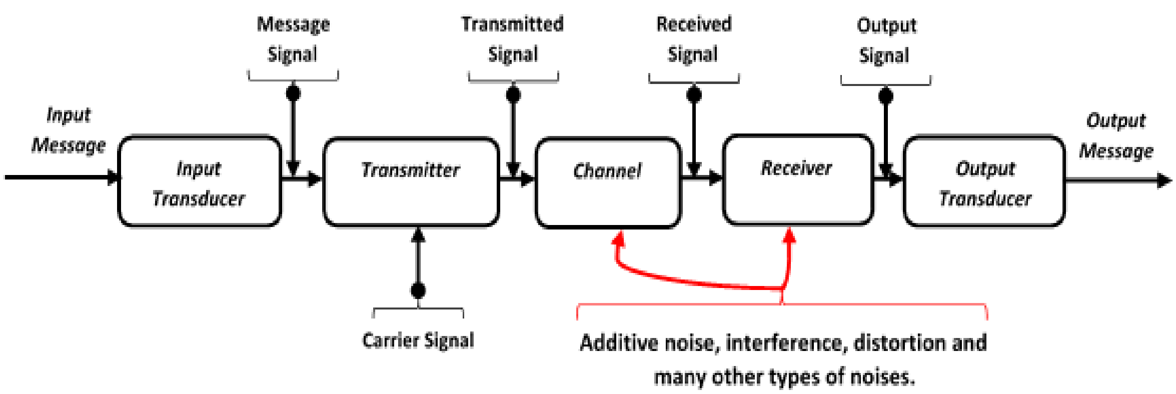


Figure 1. 1: General Communication System Block Diagram.

1.1.1 Input Transducer:

A transducer is a system or a sensor that has ability to convert energy from one form to another which is suitable for the next processing stages (Rodger E & William H, 2015). E.g.: in wireless communication systems, end-user voice or data signals are translated to voltage differences via a microphone. And such translated signals are called as the message signal.

1.1.2 Transmitter (Tx):

The key purpose of the transmitter is to prepare the input signal by using appropriate processes such as modulation to be transmitted across long distances over the available transmission medium (Freeman, 2005). The primary block in the transmitter section is the modulator which perform modulation: modulation is the methodical variation of any of the carrier's characteristics, such as amplitude, phase or frequency, in line with the message signal function despite the fact there are many reasons to use and modulate a carrier (Rodger E & William H, 2015).

1.1.3 Channel:

The channel it is also known as the transmission medium; the transmission medium can one of two main types Guided mediums such as copper cable, fiber optic cables and Unguided mediums such as Radio Waves (Rodger E & William H, 2015; Freeman, 2005). The transmitted signal in this channel propagates across the guided or unguided media.

Even though there is one thing in common with both channels: that the signal is diminished from transmitter to receiver. While this deterioration can occur at any stage in the block diagram of the communication structure, the channel itself is typically can cause losses. This loss mostly results from noise and other disturbances or unnecessary signals, but can also involve other consequences of amplification, and fading signal speeds, multiple propagation paths, and filtering disruptions (Sibley, 2018).

1.1.4 Receiver (Rx):

The receiver's function is to extract the desired message from the received signal by the channel output and to convert it to a form suitable for the output transducer. The main block in the receiver side is the demodulator which demodulate the received signal to baseband version (Freeman, 2005).

1.1.5 Output Transducer:

The output transducer is the last block in any communication model. At its input, this instrument transforms the electrical signal into a form appropriate for end-user specifications, where voice or data types are the most typical forms of the output transducer (Freeman, 2005).

1.2 Cellular Communication Systems History:

First Generation of cellular comm-systems was designed to use FDMA as the multiple access technology. FDMA depends mainly on Frequency Modulation which is analog transmission technique that has inherently narrowband and it is used for speech transmission.

The 1G has satisfied the basic mobile voice conversation; it was an analog cellular technology with limited coverage and limited number of users. The Second Generation of cellular systems was primarily digital transmission system (Sibley, 2018).

This system uses either TDMA or/and CDMA as multiple access technology. Although, the 2G offered higher transmission rate with greater flexibility than the 1G system, they are nevertheless, narrowband systems. 2G has introduced decent capacity and coverage. As it provides facilities like fast messaging and has lower rapidity data using digital multiple access. The 2G was succeeded by upgrading it to third generation (2.5G) which is EDGE for offering higher data rates (Glisic & G., 2006).

The 3G standard is based on CDMA with a transmission rate up to 2 Mbps, that is wideband and are expected to support multimedia services. This revolutionized the mobile services with a real mobile broadband, in which this laid foundation for the 4-generation. The 4G can offer connectivity to a broad spectrum of telecommunications facilities, including advanced broadband technologies, enabled by increasingly packet-based mobile and fixed networks, as well as support for low to high mobility applications and a wide variety of data rates.

In line with market demands in the multi-user world, whereas future system is based on user demands as the 4G cellular system applications need high data rates activeness (Sibley, 2018). Which it is done by transforming the high-rate serial data sequence into a number of parallel data sequences with a lower rate and then modulating each one into a multiplex form, OFDM multiplexing orthogonal frequency division is an important way to accomplish this concept (PENTTINEN, 2015).

Due to its critical position in wireless networking technologies, OFDM has attracted a great deal of researchers' interest. OFDM is an important technique for wireless communication systems because of its advantages such as large spectral efficiency, increased data rate capacity of the individual subcarrier according to signal-to-noise ratio (SNR), robustness in frequency selective fading paths, overcoming inter-symbol interference and the ability to accommodate very heavy multi-path fading (Glisic & G., 2006).

1.2.1 Summary of Wireless Communication Systems Evolutions:

Table 1. 1: Summary of Cellular Systems Evolution.

Parameters	1G	2G	3G	4G	5G
Tech-type	Analog	Digital-CS	Digital-PS	Digital	Digital
Data-rates	9.6 -15 Kbps	9.6 Kbps -115 Kbps	2 Mbps	20 - 40 Mbps 0.1-1 Gbps	1-10Gbps
Mul-Access	FDMA	TDMA/CDMA	CDMA	OFDMA	OFDMA/NOMA
Frequency	800 MHz	800 MHz/1.9 GHz	2GHz	2GHz	4-100GHz
CH-spacing	30KHz	200KHz	5 MHz	18MHz	18/20MHz

1.3 Orthogonal Frequency-Division Multiplexing:

Orthogonal frequency-division multiplexing (OFDM) communication scheme is a type of a multicarrier scheme, which employs multiple orthogonal subcarriers to carry the end-user data from source to the destination where bandwidth efficiency is attained by the process of superimposing the bands of orthogonal subcarriers. The FF-transform (FFT) and inverse-FT (IFFT) methods are suitable for realizing these ortho-signals (Cho, Kim, Yang, & Kang, 2010). In OFDM TRX-scheme an $n - point$ inverse-FT is used for encoding $X[k]$ Tx-symbol to generate $x[n]$ sample. So, take into account $y[n]$ as the received data sample which resembles $x[n]$ transmitted symbols plus an additive noise $w[n]$ due to the channel properties (Cho, Kim, Yang, & Kang, 2010), Hence:

$$y[n] = x[n] + w[n] \quad \textbf{(1.1)}$$

Then by considering the reverse process of taking $n - point$ Fast-FT of the Rx-symbols, $y[n]$, we obtain a chattering form of the communicated symbols $Y[k]$ at the receiver (Cho, Kim, Yang, & Kang, 2010).

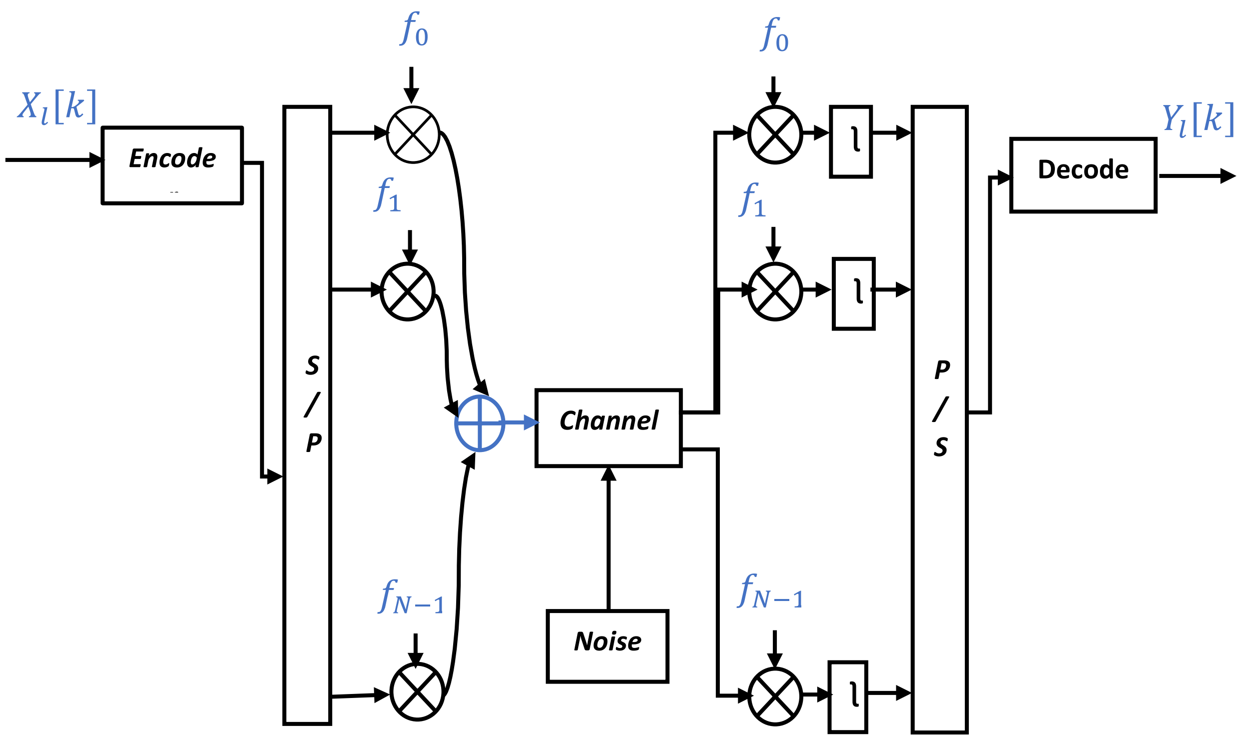


Figure 1. 2: Outline of OFDM Transmission Scheme.

As we know all the orthogonal subcarriers are having a determinate period T, thus the OFDM data-signal spectrum can be considered as the frequency-shifted *Sinc* functions summations in the frequency domain as shown in Figure (1.3) below, where the overlapped adjacent *SC-Sinc* equations are spaced by $\frac{1}{T}$ (Cho, Kim, Yang, & Kang, 2010).

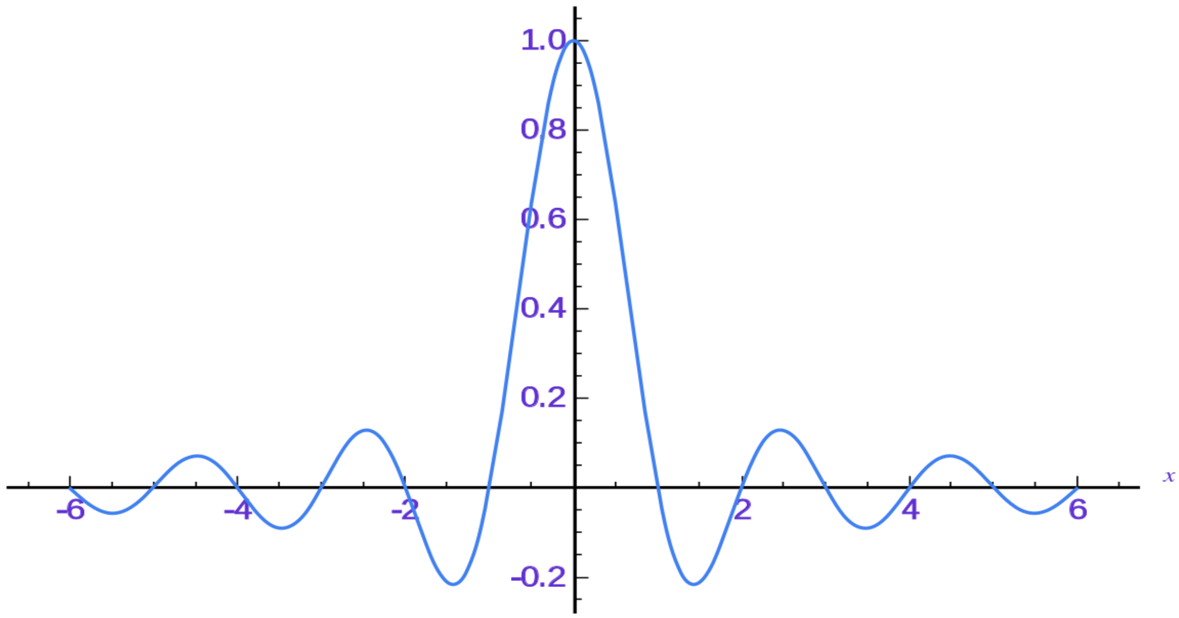


Figure 1. 3: Spectrum of OFDM Signal (Sinc Functions).

1.4 Orthogonality:

If we consider the complex exponential signals that are time-confined, as $e^{j2\pi f_k t}$ which signify the various subcarriers at $f_k = \frac{k}{T_{sym}}$, while $0 \leq t \leq T_{sym}$. such data-signals are demarcated as ortho-signals if their integral of the products along their fundamental period is zero (Cho, Kim, Yang, & Kang, 2010), which means,

$$\frac{1}{T_{sym}} \int_0^{T_{sym}} e^{j2\pi f_k t} e^{-j2\pi f_i t} dt = \frac{1}{T_{sym}} \int_0^{T_{sym}} e^{j2\pi\left(\frac{k-i}{T_{sym}}\right)} dt \qquad \textbf{(1.2)}$$

$$= \begin{cases} 1, & \forall \quad k = i \\ 0, & Othrwise \end{cases} \qquad \textbf{(1.3)}$$

Taking separate samples with instances of sampling at $t = nT_s = n\frac{nT_{sym}}{N}$, $n = 0,1,2, \ldots, N-1$, In the discrete time domain, the above equation can be written as:

$$\frac{1}{N}\sum_{n=0}^{N-1} e^{j2\pi\frac{k}{T_{sym}}nT_s} e^{-j2\pi\frac{i}{T}nT_s} = \frac{1}{N}\sum_{n=0}^{N-1} e^{j2\pi(\frac{k-i}{N})n} \quad \textbf{(1.4)}$$

$$= \begin{cases} 1, & \forall \quad k = i \\ 0, & Othrwise \end{cases} \quad \textbf{(1.5)}$$

The above Equation (1.2) and (1.4) are the essential orthogonality condition for OFDM signals in continuous time and discrete time domains.

1.5 Modulation/Demodulation In OFDM:

The transmitter portion of the OFDM transforms the bits of the input signal into a series of M-PSK/M-QAM packets which that is going to be mapped afterward into N-parallel data-streams where every N- symbols obtained by using the S/P mapping stage which is conducted on numerous subcarrier that are available (Cho, Kim, Yang, & Kang, 2010). Thus, let $X_l[k]$ represent the l^{th} transmit symbol at the k^{th} subcarrier. Where the transmission time length for N-Symbols is NT_s forming a single duration of the OFDM packet duration with a period length T_{sym} and T_{sym} = NT_s we get the baseband OFDM transmitted signal in continuous time domain (Cho, Kim, Yang, & Kang, 2010). And that is given as:

$$x_l(t) = \sum_{l=0}^{\infty}\sum_{k=0}^{N-1} X_l[k]e^{j2\pi f_k(t-lT_{sym})} \quad \textbf{(1.6)}$$

In the latter equation (1.6) , the continuous-time OFDM baseband signal sampling ca be done at $t = lT_{sym} + nT_s$ while $T_s = \frac{T_{sym}}{N}$, $f_k = \frac{k}{T_{sym}}$ produce the discrete-time matching baseband OFDM character (Syms) as:

$$x_l[n] = \sum_{k=0}^{N-1} X_l[k]e^{\frac{j2\pi kn}{N}} \quad , for\ n = 0, 1, 2, \dots, N-1 \quad \textbf{(1.7)}$$

Note that the above Equation (1.7) is the $n - point$ IFFT of Phase shift keying, Quadrature-AM data packets $X_l[k]$. Thus, consider the baseband OFDM character obtained:

$$y_l(t) = \sum_{k=0}^{N-1} X_l[k] e^{-2\pi f_k (t - lT_{sym})} \quad \textbf{(1.8)}$$

$$where \longrightarrow \quad lT_{sym} < t \leq lT_{sym} + nT_s$$

By using the definition of orthogonality between the subcarriers, the transmitted symbol $X_l[k]$ can be reconstructed as follows:

$$Y_l[k] = \sum_{i=0}^{N-1} X_l[i] \left\{ \frac{1}{T_{sym}} \int_0^{T_{sym}} e^{j2\pi(f_i - f_k)(t - lT_{sym})} dt \right\} = X_l[k] \quad \textbf{(1.9)}$$

Channel impacts and noise are not taken into consideration. Let $y_l[n]$ at $t = lT_{sym} + nT_s$ be the sample values of the obtained OFDM symbol $y_l(t)$. Then, the integration of the above equation into the modulation phase can be expressed in the discrete time period (Cho, Kim, Yang, & Kang, 2010).This is illustrated as follows:

$$Y_l[k] = \frac{1}{N} \sum_{n=0}^{N-1} \sum_{i=0}^{N-1} X_l[i] e^{\frac{j2\pi(i-k)n}{N}} = X_l[k] \quad \textbf{(1.10)}$$

Thus, the Equation (1.10) is the $n - point$ Discrete-FT of $y_l[n]$ which can be easily calculated by using the Fast-FT algorithm (Cho, Kim, Yang, & Kang, 2010).

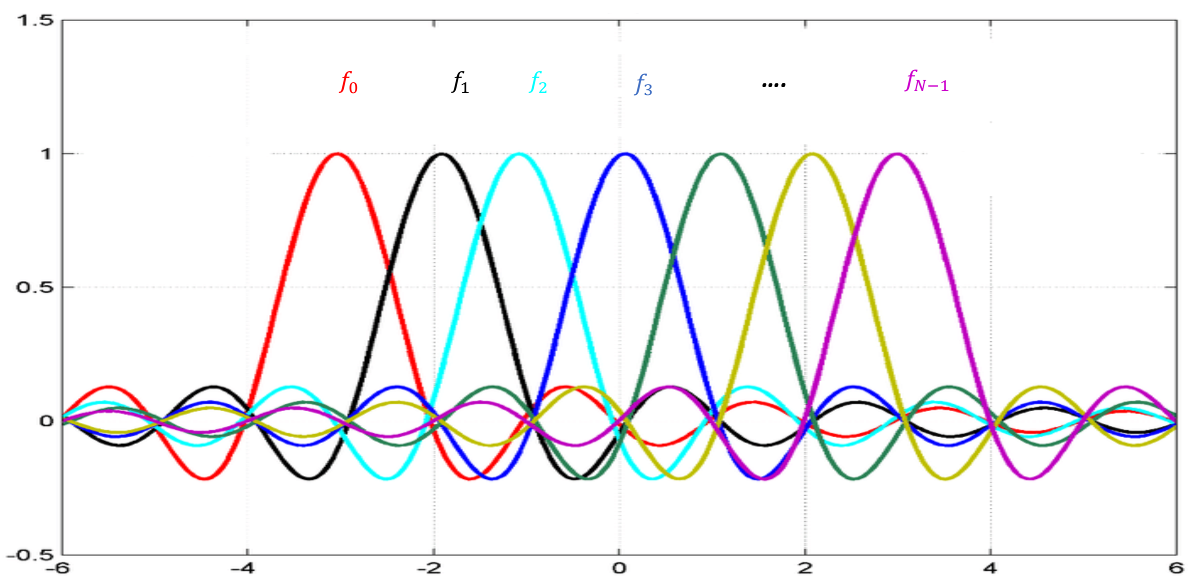


Figure 1. 4: Concept of Subcarriers Orthogonality.

1.5.1 OFDM Modulation and Demodulation Block Diagram:

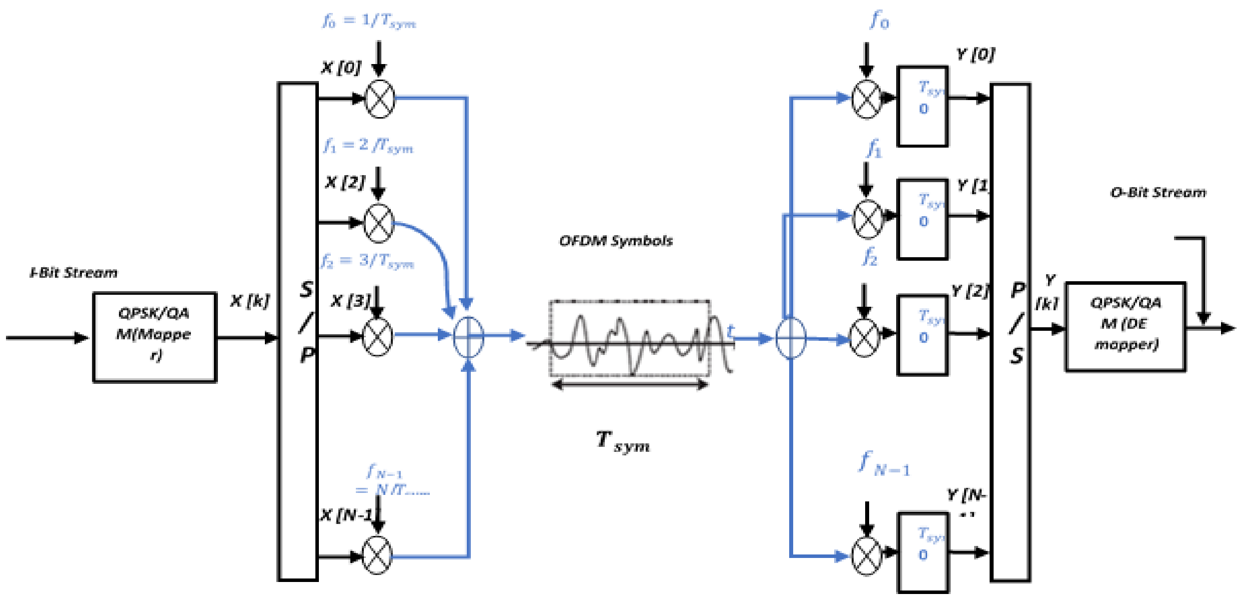


Figure 1. 5: OFDM Modulation and Demodulation Block Diagram.

1.5.2 OFDM Transmitter and Receiver Block Diagram:

OFDM scheme have an input signal in from of the serial data which is then prearranged into parallel set-up to reduce the bit-rate/subcarrier. This parallel signal is transformed using any acceptable form of modulation, such as M-QPSK or M-QAM. As an outcome, there can be very high values for the amplitude of such a signal.

This large difference in amplitude is an immense OFDM disadvantage that tends to decrease the power amplifier's efficiency. Since the amplifier for high input amplitudes is typically very non-linear, it may be necessary to reduce the input impedance to decrease the distortion.

The reduction of additional power is based on the reduction of the signal deformity based on PAPR reduction and other factors. N-overlaps orthogonal sub-carriers in this method, each carrying a *1/T* baud rate and *1/T* spaced apart, such sub-carrier orthogonality requires that each sub-carrier has precisely the same integer number of cycles in the interval *T* (Cho, Kim, Yang, & Kang, 2010). Therefore, to preserve orthogonality between the sub-carriers, the Inverse Fast-FT block is given and used, which is properly decoded with a Fast-FT block on the receiver side. The OFDM Transmitter/Receiver system diagram is shown in Figure (1.6) below:

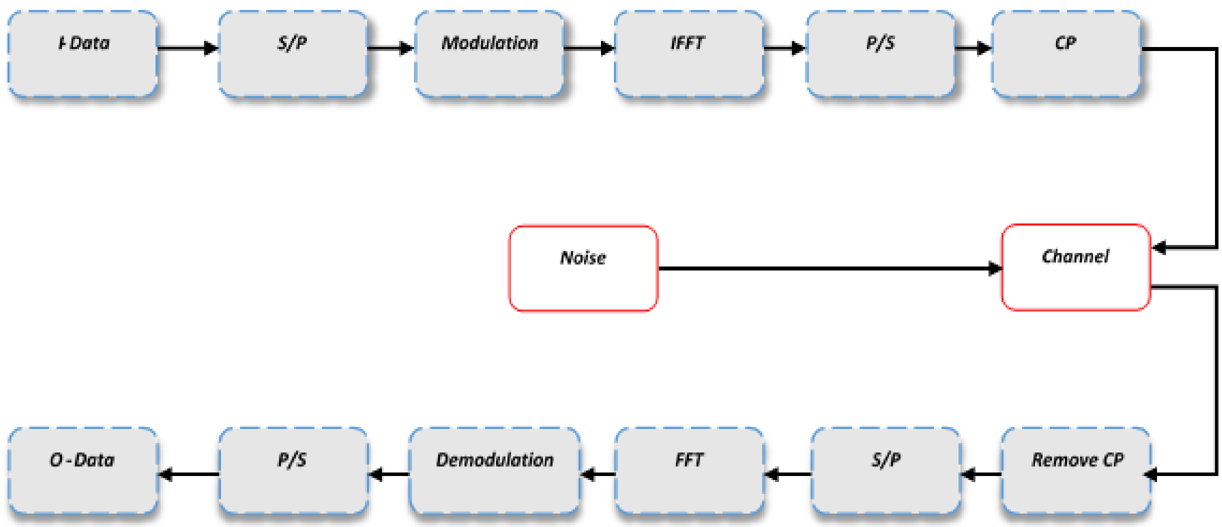


Figure 1. 6: Block Diagram for OFDM Transceiver System.

When looking at the transceiver block diagram above, the input signals are encoded using serial/parallel converter block where such signals are translated to parallel signals. Then these signals are modulated with the assistance of QPSK Or QAM Modulator. The IFFT block then absorbs the modulated signal where the Inverse Fast-FT converts this signal into a time domain signal, preserving the orthogonality of the OFDM data transmitted through the channel after that CP is inserted. The key reasons for making a CP block in the transmission path are that a Cyclic Prefix (CP) or guard interval is applied to the transmitted symbols to minimize the interference between the neighboring OFDM symbols and also to preserve the orthogonality between the subcarriers. Although the length of this CP is set aside as greater than or equal to the redundancy of the channel length. As a consequence, inter-symbol (ISI) interference is absolutely eradicated. The resulting symbols are then added to a P/S and sent through the channel (Cho, Kim, Yang, & Kang, 2010; Govil, 2018).

The data is obtained from the wireless channel on the receiver side and received by the receiver, then the CP or guard interval is removed from the OFDM symbol. The data is then mapped back from serial to parallel. This parallel data is then converted from the time domain to the frequency domain signal by using the Fast-FT block. Further demodulation and encoding of the signal are performed. Therefore consider $X = (X[0], X[1], \dots, X[N-1])$ is a modulated data sequence of length N. Where $X[k]$ is the transmitted symbols, Then the complex envelope of the received and demodulated baseband OFDM signal for N carrier (Cho, Kim, Yang, & Kang, 2010), Which is given is given as:

$$x(t) = \sum_{k=0}^{N-1} X[k] e^{\frac{j2\pi kt}{T_{sym}}} \tag{1.11}$$

1.6 Fifth Generation wireless Communication Systems:

5G it refers to the cellular communication 5th generation, it is a novel comprehensive cellular norm developed as a successor to the current 4G cellular communication system. 5G networking makes a revolutionary form of network that links almost anything that has an IP address and interacts together, including individuals and apparatuses. 5G cellular tech is a sophisticated multi-Gbps topmost data-rates, Very-low delays and better stability are intended to be delivered to more devices, plus huge network bandwidth, which improved availability and add more uniform user interface (Qualcomm, n.d.).

1.6.1 Fifth Generation Main Features:

The important distinct features of the fifth generation of cellular communication system are shown in the following chart:

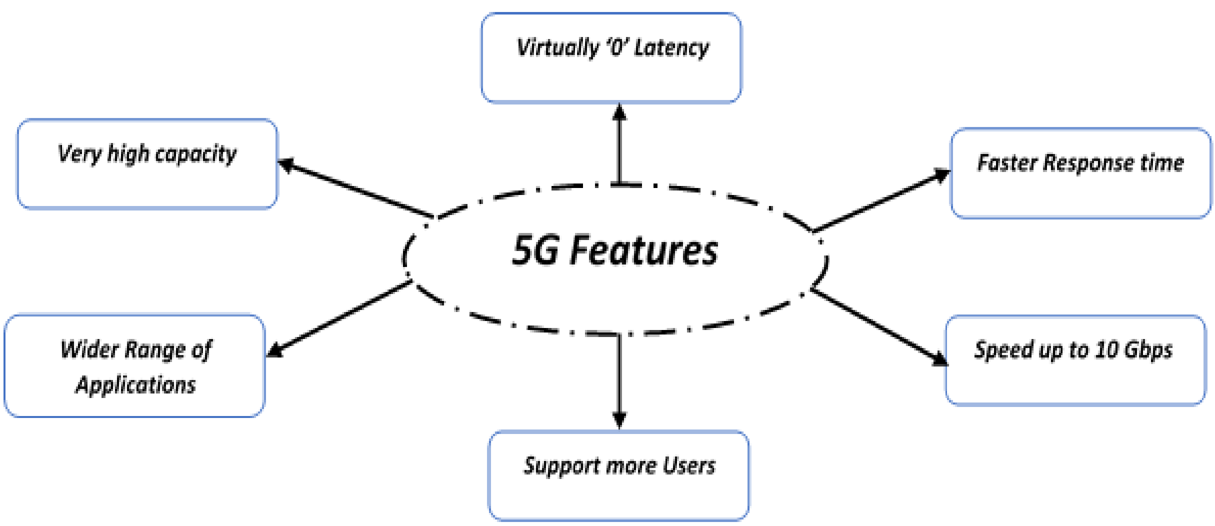


Figure 1. 7: 5G Important Features.

1.6.2 Fifth Generation Contributory Technologies:

5G is based on the concept of Ortho-frequency division-multiplexing schema and other important technologies which will be illustrated in the following paragraphs, OFDM is a way of modulating a digital signal through many different channels to decrease fifth generation interference (Qualcomm, n.d.). 5G uses 5G-NR interface alongside OFDM principles to support the new requirements demanded by this new technology (K, 2018). The new 5G-NR can additionally improve OFDM schema and logic to transport a sophisticated grade of scalability plus elasticity, as this technology would facilitate access to more customers and facilities with a number of diverse use cases (K, 2018).

By the usage of new spectrum regions, 5G will utilize and use larger bandwidths, which will enable the use of spectrum varieties of sub 6 GHz and 4G to 100 GHz (ETSI, 2018). Extreme low latency, high bandwidth and multi-Gbps throughput would be transmitted (ETSI, 2018).

1.7 Motivation:

The growing number of cellular devices users and the hunger for more data consumption has been the main reason to bandwidth exhaustion, and developments of wireless communication system. Therefore, in order to handle such extreme demands, researchers purposely increased the efficiency and capacity of wireless communication systems through the development of successive generations of our cellular communications systems.

Wireless communication researchers may have developed a lot of wireless channels estimations methods. Because a highly accurate channel estimation models are necessity for practical wireless system design and simulation.

Therefore, the motivation of this master thesis is to develop a machine learning-based channel estimation models, which are able to extract key channel features and use them for user data recovery at the 5G cellular receiver side.

Hence our aim is to design a more accurate channel estimation model with the assistance of deep learning LSTM method for 5G communication system simulations in MATLAB.

1.8 Thesis objectives:

Taking into account the main objectives of this thesis-work listed as below these objectives focuses on the implementation of channel estimation generated for 5G cellular comm-systems where the orthogonal-FDM as the back bone for the 5G communication arrangement constructed by utilization of the new 5G NR plus 3GPP specifications:

- A comprehensive study of the channel estimation base-line methods.
- Design and validation of a deep learning model to estimate 5G using MATLAB and Python environments.

- Testing and verification of the designed model performance and accuracy.

1.9 Thesis structure:

This thesis workload has been divided into six chapters. The first Three chapter illustrate the foundation theory and content required for attaining the purpose behind this work. Chapter four clarifies the design methodology and the implementation of the thesis objective. Chapter five demonstrate the process of testing and validating the designed model. Chapter six shade the lights on the obtained results and future scope of this thesis.

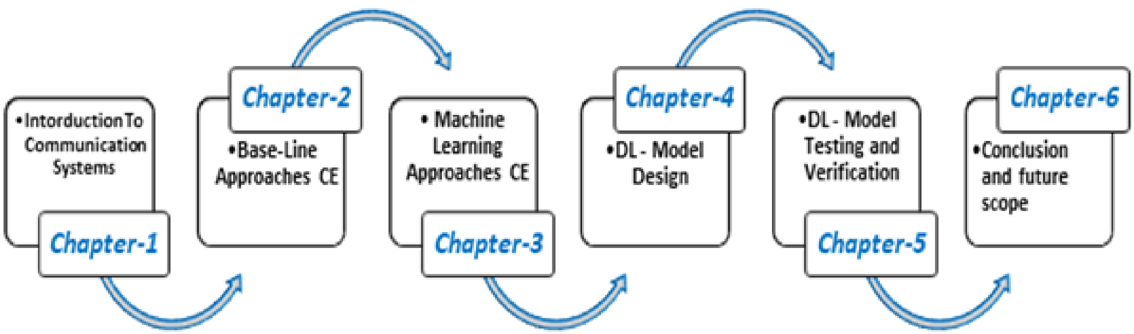


Figure 1. 8: Thesis Structure.

1.10 Problem specification and main contribution:

There are two main key difficulties that we can encounter while designing channel estimation model for cellular 5G communication system. The first difficulty is the gathering and generation of the correct and sufficient 5G data. The other challenge is the development of a channel predictor with equally tolerable intricacy and decent-performance features. Thus, the channel estimation model should have a mazing performance and high accuracy. Therefore, this thesis answer question:

How can we design the Deep-Learning channel estimation model that have tow main characteristics as: performance with high accuracy through the study and modification of previous art being done in this area?

1.11 Summary of the principal contributions:

- To design a channel estimation model using deep-learning approach for5G communication with good performance and high accuracy.

- Evaluate the channel estimation deigned model computational accuracy.
- Simulation results of the proposed methods provide comparative study and validate proposal.

2. Channel Estimation and the Current State of Art

2.1 Concept of Communication Channel:

A channel is defined as a path provided by a transmission medium and the transmission mediums can be of two main categories either a guided transmission medium such as copper wires and fiber optics cables or unguided transmission mediums such as radio frequencies (Roger & Freeman, 2006).

2.1.2 Radio Channel:

A radio channel is known as a radio frequency band or range used for carrying the user information between source and destination (Lathi & Ding, 2010). A radio channels are usually allocated for a specified type of a radio communication system depending on the application such cellular communication radar communication and so on (Roger & Freeman, 2006).

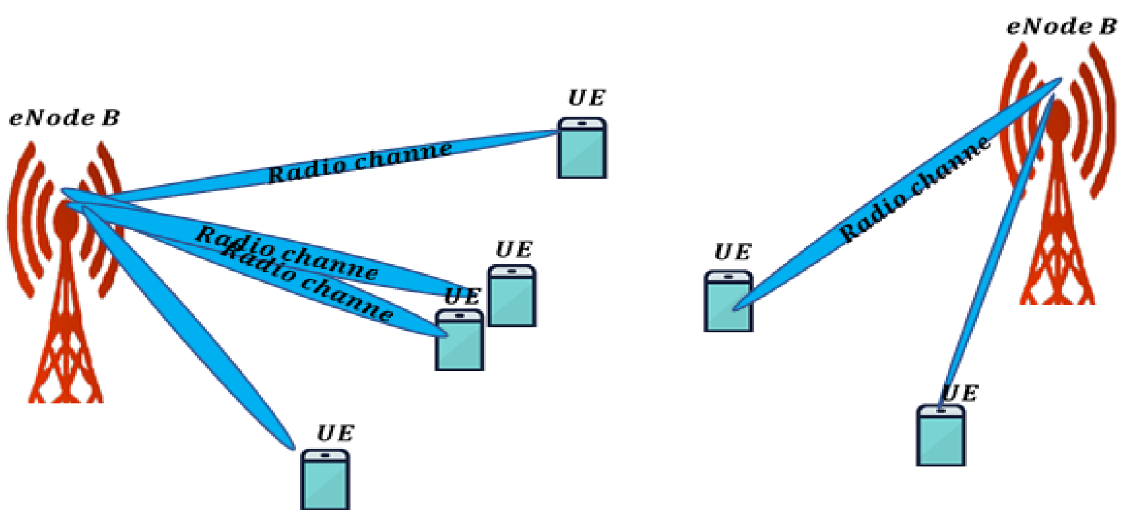


Figure 2. 1: Concept of Radio Channel.

2.2 Literature Review:

This section of the Thesis-1 introduces a literature survey that we have done in the area of 5G communication systems plus related method used for channels estimation. The significant of this survey lies on providing us with an idea about the accomplished work and the recent situation of research in this field; more less, it exposed us to see how vast this area is and how far it can go in the future. This survey backing us to classify our project under the category of Channel Estimation Using Deep Learning for 5G Communication Systems, in addition it organize our thought to achieve our aim, and perceive the big picture of this area. Only certain papers, based on their relevance and influence to our thesis, will be presented in this section.

According to (Ye, Li, & Juang, 2018), This work presents a DL strategy for orthogonal frequency-division multiplexing channel estimation and signal detection. Thus, they use the principle of DL “deep learning” in this paper to control wireless O-FDM calculation of channels from end to another end approach.

Unlike current OFDM TRX which directly approximation channel state info (CSI) first and then use the appraised CSI to recover/detect the transmitted data-sym, the proposed DL-based method here indirectly guesses CSI and recovers the transmitted data directly by designing a DL model firstly, train it offline using the data generated from simulation based on channel info and then use it for recovering the required online transmitted data directly.

In (Yuan, Hien Q, & Matthaiou, 2019), considering this research the proposed design of a ML “machine-learning” scheme created based on time-division duplex method in which channel state data can be attained by manipulating the correlation of the temporal channel to overcome the excessive overhead expanse required in ortho-pilot data for conventional CE methods. The proposed machine learning predictors include a pattern extraction and CSI-predictor which can be applied either by a convolutionary neural network (CNN) and AR predictor or through an exogenous inputs recurrent neural network (NARX-RNN) autoregressive network.

In (Wen C, Wan T, & Jin, 2018), This work consists of the use of a DL techniques to build a “CsiNet”, CsiNet is a novel channel state info (CSI) sensing/retrieval method which learns to use channel structure efficiently from training data points.

CsiNet learns a conversion from CS-info to an almost optimum number of depictions (code data) and an inverse conversion from coded data to CS-info, which aim at reducing the excessive feedback overhead used by conventional CSI method for channel estimations and in turn can be used for data recovery.

According to (Apelfröjd, Björsell, Sternad, & Phan-Huy, 2018), In this research Kalman filter is used to obtain smoothed interpolation estimates of the downlink channels of a TDD system, based on uplink channel estimates. In order to perform smoothing, future measurements of the channel need to be available to the filter. This can be achieved for vehicular user equipment by placing an antenna system as, a predictor antenna, in front of a second prime antenna, the main antenna, on the roof of a vehicle in the direction of travel. Whereas the predictor antenna will then experience the channel before the main antenna and can hence collect (future) measurements of the channel for the main antenna.

Interpolation of the uplink channel needs to be performed over the duration of downlink slots, in which no uplink pilots are available. The quality of the interpolation performance influences the quality of the channel estimates of the downlink slots on which downlink transmission and beamforming is based. A good interpolation scheme will allow a longer downlink slot duration to be used for mobile users.

In (Lyu, Z, J, Q, & Z., 2018), Here three types of neural network designs were proposed by the authors: multi-layer perceptron (MLP), convolution-NN (CNN) and recurrent-NN (RNN). Through extensive simulation, the performance of these deep neural networks is assessed. Where the numerical results show that RNN has the best performance of decoding, but at the price of the highest overhead of computation usage. In addition, for each type of neural network, they found that a saturation length exists, which is caused by the methods limited learning abilities.

According to (Motade & Kulkarni, 2018) This research suggests the design of an algorithm for finding pilot pattern which significantly improves the results of CE in terms of MS-error (MSE), symbol rates of error (SER) and channel detection bit rate of errors. The optimal location of the pilot reduces the computational difficulty and maximizes the system's precision. For the proposed method, the performance of the channel estimation and multi-user identification was good as it produced significant results, which were confirmed by simulations.

In (Sneha K & Ankit, 2017), according to this work Miss. Sneha Kumari and Mr. Ankit Tripathi, have implemented OFDM communication system by using different modulation approaches such as QPSK, QAM, 16PSK and BPSK. Then they have evaluated the erroneous rate of data bits (BER) to SN-ratio (SNR) of the individual modulation scheme mentioned above. The channel used is Rayleigh fading Channel, for this research. Hence according to this work the lower the modulation coding scheme the higher the bit rate free of error efficiency of the scheme.

According to (Farzamnia, Ngu, M, & Manas K, 2018), The researchers have investigated, The BER output of OFDM beside using M-QAM and Rayleigh/AWGN channels. Thus, they have studied and compared the results of 4QAM, 16QAM, and 64QAM modulation techniques when utilizing Rayleigh fading channel. They have found that while studying the BER of above modulation systems they have found the 4QAM have the lowest BER performance in comparison to 8QAM and 16QAM. The findings of this paper also show that a modulation scheme with lower constellation points has a higher BER accomplishment. Then, they have studied and simulated the performance of QPSK modulation system and compared it with the performance of QAM modulation scheme, and the result of QPSK shows a lower BER in comparison to the result of QAM modulation scheme.

In (Abdelhamid, Mohamed, & Moha M'Rabet, 2019), The authors have performed a CE by using least squares "LS" as a ZF and MMSE predictors for a massive MIMO scheme joint with an upper order modulation for OFDM method. Which led to a conclusion as when increasing the number of constellation points in a modulation system causes an increase in the method sensitivity with respect to noise. Consequently, with a use of large number antenna at the receiver they compensated for the noise responsiveness and increased the method capability.

The literature (Yao, Wang, Zuo, Xu, & Qi, 2019) presented a DL assisted data detection approach for OFDM schema with time-varying channels. Thus, they have proposed and designed a deep neural network model to perform channel estimation for an OFDM arrangement when the system has a time-varying channels. The simulation results show that this suggested method based on DL is feasible and has outstanding recital capability. This model can therefore be used with a high degree of reliability in practice.

2.3 What is Channel Estimation:

As we know in all communication the transmitter signal travels through a medium often called as the channel and the transmitted signal gets deformed by numerous forms of noises and clatter gets added to the Tx-data due to the channel characteristics (Kim, 2017). Therefore, to properly decode and recover the transmitted signal at the receiver the removing of the distortion and noise by the channel properties this is main goal behind all channel estimations methods (sharetechnote;, 2020).

The first step is to study the properties of the medium into which the signal has passed in order to retrieve the original transmitted signal from the receiver. The method/methods used to describe the channel is thus referred to as channel-estimation (CE). As seen below this signal deformity mechanism in the figure (2.2):

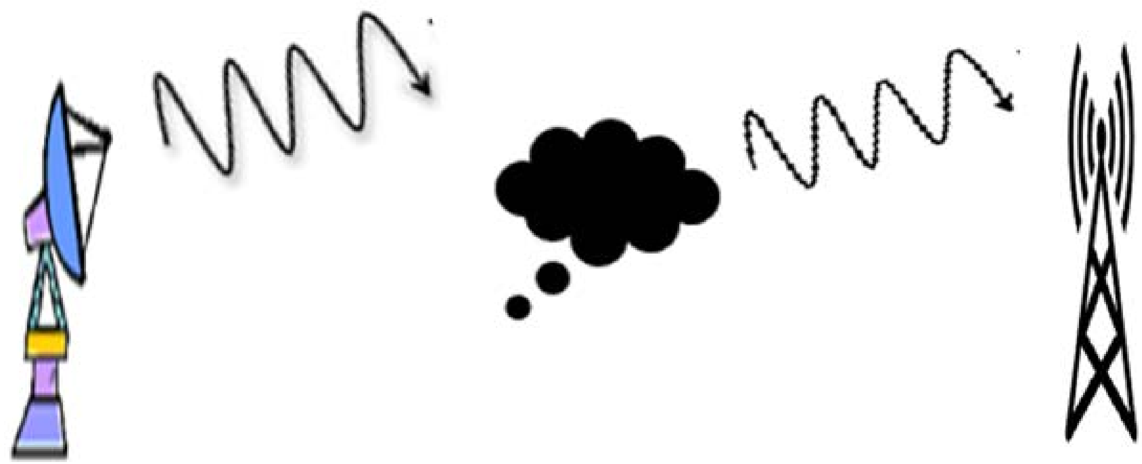


Figure 2. 2: Wireless Channel Estimation Degradation.

2.4 Types of Channel Estimation techniques:

Channel estimation approaches can be classified into three broad categories as follows (Josh Patterson, 2018; Fumo, 2017):

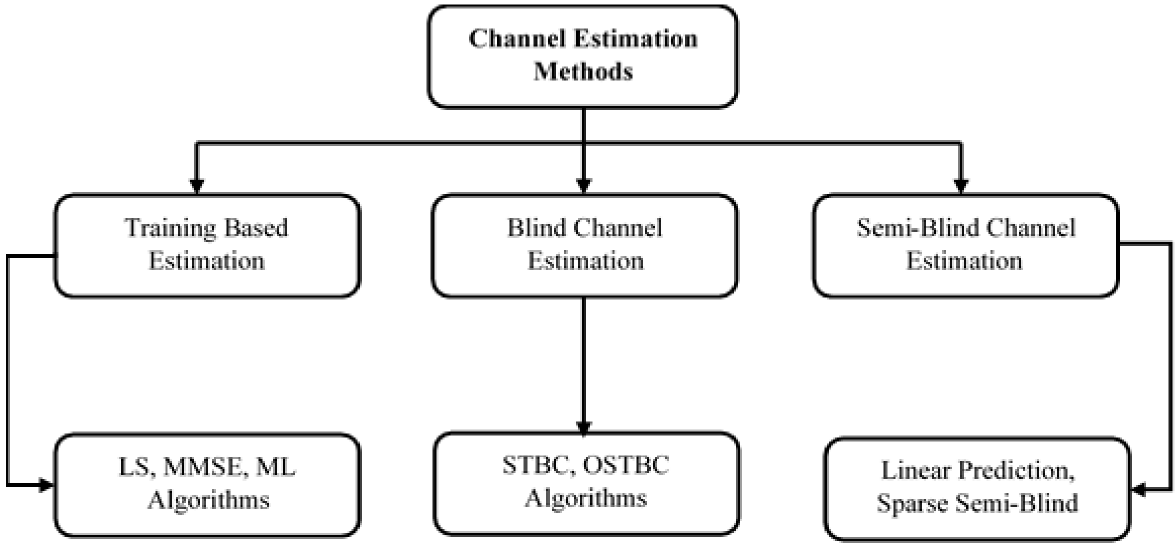


Figure 2. 3: CE Methods.

2.4.1 CE-Baseline Techniques:

The base line channel estimations methods which all the other approaches consider in the process of building or designing a new channel estimation model are:

- Least Square Error method (LS).
- Minimum Mean Square Error method (MMSE)

These base line methods use the concept of training pilots where the training points can be used to perform CE, they deliver a reasonable output, but their transmitting effectiveness are diminished because of the required overhead of training points that are often referred to as preamble or pilot symbols that are transmitted alongside the data symbols in accumulation channel. When the training data are available, the least-square (LS) and minimum-mean-square error (MMSE) approaches are widely used for CE (Cho, Kim, Yang, & Kang, 2010).

These methods as baseline channel estimation methods transmit an established signal typically referred to as a reference signal / pilot signal by either inserting such signals into all of the subcarriers of orthogonal frequency division multiplexing system symbols at a pre-specific periods or by interleaving the reference pilots signal into each orthogonal frequency division multiplexing symbol mainly to compensate for input data losses in T-domain or in F-domain or in both domains simultaneously thus, depending on this idea of where and when to insert the training data we have three main types of pilot structures illustrated in the next section.

2.5 Training symbols Insertion Methods:

Generally training symbols insertion methods are classified into three main types which are block type of pilots insertion, comb type of insertion and lattice type of pilot symbol insertion hence all these three types are explained in details as shown below (Cho, Kim, Yang, & Kang, 2010).

2.5.1 Block-Type Pilot Arrangement:

A block-type of pilot insertion structure which is used in particular cases of signal recovery is shown in the following figure (2.4) below:

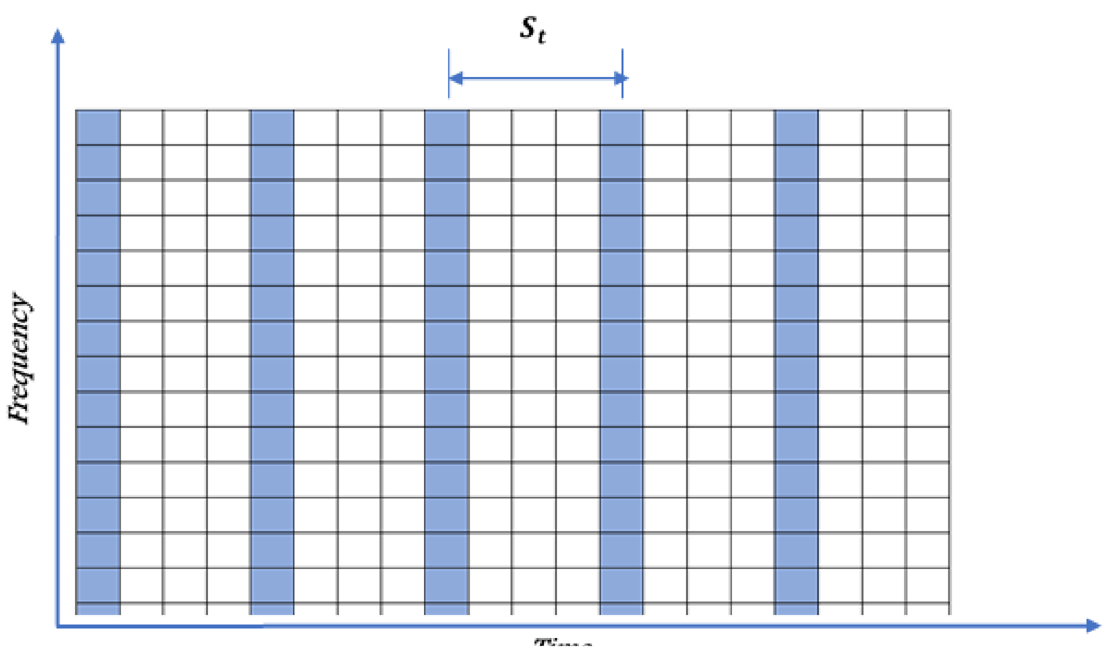


Figure 2. 4: Pilot- Block Type-Structure.

Considering this block type pilot insertion, the pilot's tones are implanted at complete orthogonal frequency division multiplexing symbols period on whole subcarriers and are regularly broadcast for CEs. Through the use of such insertion method, to approximate the channel along the time domain axis, a time domain interpolation may be performed.

Thus consider S_t represent the time cycle of pilot data in time-domain, thus the pilot points must then be initiated as often as the coherence time is (Cho, Kim, Yang, & Kang, 2010). If the coherence time in the channel is given as the inverse form of the Doppler frequency f_{dop} the pilot-sym length must then satisfy the following inequality equation (Cho, Kim, Yang, & Kang, 2010):

$$S_t \leq \frac{1}{f_{dop}} \qquad \textbf{(2.1)}$$

Since pilot data-sym are introduced with a time span along whole subcarriers, the block-type pilot arrangement is ideal for frequency-selective channels, which helps to monitor the features of the t-varying channel.

2.5.2 Comb-Type Pilot Structure:

The following figure (2.5) indicates a Comb-type of pilot system used in particular cases of signal recovery:

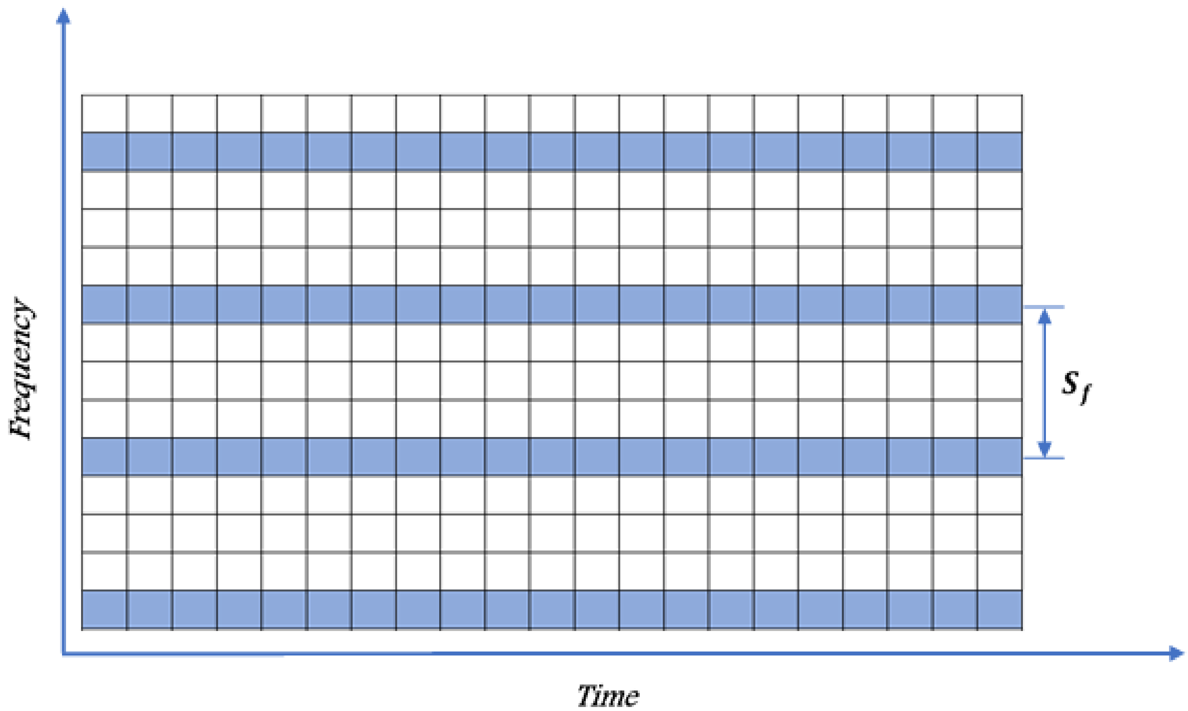


Figure 2. 5: Comb-Type Pilot Structure.

Each orthogonal frequency division multiplexing symbol has pilot tones that are periodically placed at whole subcarriers in this comb-pilot insertion system. Thus, this kind of arrangement is used to accomplish C-estimation along the frequency axis, to attain freq-domain interpolation. So, let S_f be the period of pilot signals in frequency (Cho, Kim, Yang, & Kang, 2010).

The pilot symbols must also be put as consistently as coherent bandwidth to keep track of the freq-selective channel features, if an inverse of the maximum delay spread σ_{max}, defines the coherence band-width, the pilot points duration must then fulfill the following equation (Cho, Kim, Yang, & Kang, 2010):

$$S_f \leq \frac{1}{\sigma_{max}} \tag{2.2}$$

The comb-pilot type approach is appropriate and targeted at identifying fast-fading channel properties, but not appropriate for freq-selective channels, as opposed to the block-pilot type arrangement system.

2.5.3 Lattice-Pilot Structure:

The Lattice-pilot insertion shown in the following figure (2.6) below is another type of pilot tone insertion:

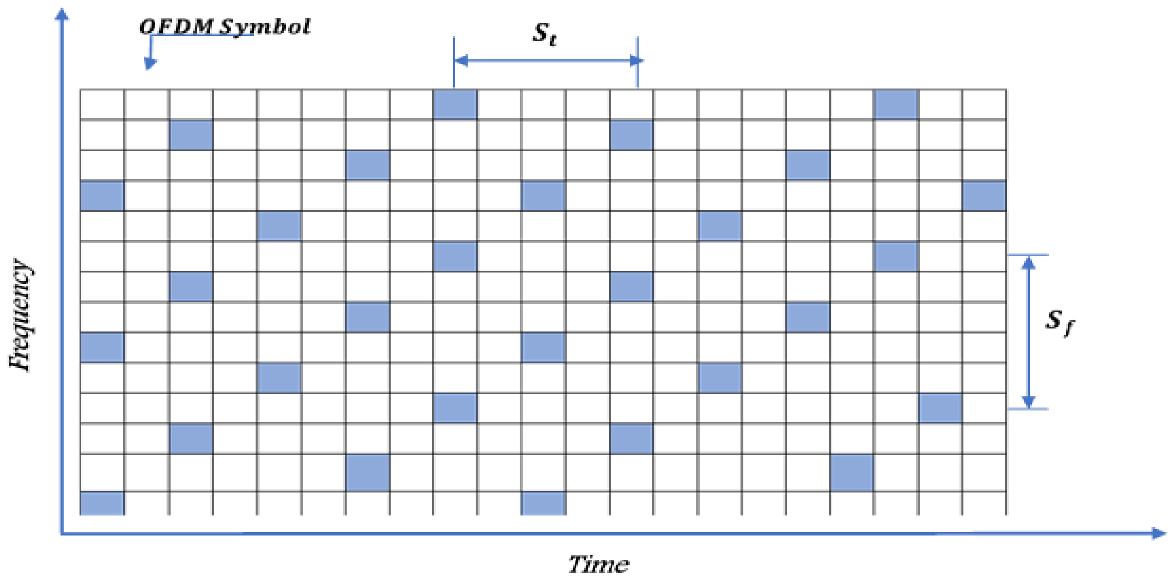


Figure 2. 6: Lattice-Type Pilot Structure.

This lattice type, the pilot bits with unique intervals are introduced along the time and frequency axis thus this system is a combination of the previous two types. Therefore, the pilot signals are distributed in the t-domain and Freq-domain axes, permitting t-domain and Freq-domain interpolations to approximate the desired channels. Thus, let S_t and S_f designate the cycles of pilot data in time and frequency, correspondingly (Cho, Kim, Yang, & Kang, 2010). Therefore, to maintain track of the Freq-selective and t-varying channel features, the pilot bits injection should fulfill the following two inequality equations:

$$S_t \leq \frac{1}{f_d} \quad and \quad S_f \leq \frac{1}{\sigma_{max}} \tag{2.3}$$

where f_d and σ_{max} Indicate the channel's doppler distribution and maximum delay spread respectively.

2.6 Mathematical Model of Training Symbols-Based C-Estimator:

Consider the training symbols is $X = \{X[0],\ X[1],\ X[2], \dots ,\ X[N-1]\}$ for $N-subcarriers$ where $X[k]$ be k^{th} subcarrier pilot data-Sym, whereas $E\{X[k]\} = 0$ and

$var\{X[k]\} = \sigma_x^2$, provided that the received training signal $Y[k]$ and channel gain is $H[k]$for each subcarrier k, (Cho, Kim, Yang, & Kang, 2010). And can be portrayed as:

$$Y[k] = X[k`]\, H[k`] + Z \qquad \textbf{(2.4)}$$

$$Y = XH + Z \qquad \textbf{(2.5)}$$

Where Z is the noise vector give as $Z = \{Z[0],\ Z[1],\ Z[2], \dots ,\ Z[N-1]\}$ with $Z\{X[k]\} = 0$ and $var\{Z[k]\} = \sigma_z^2$, also let $\widehat{H}$ represent the estimate of the channel H.

2.7 Mathematical Model of LS C-Estimator:

In order to find the channel, approximate $\widehat{H}$ the least-square (LS-CE) procedure is used to minimize the below cost function (Cho, Kim, Yang, & Kang, 2010) in equation (2.6):

$$J(\widehat{H}) = ||\bar{Y} - X\widehat{H}||^2 \qquad \textbf{(2.6)}$$

$$\min \{J(\widehat{H})\} = \min \{(\bar{Y} - X\widehat{H})^H (\bar{Y} - X\widehat{H})\} \qquad \textbf{(2.7)}$$

By equating the function derivative with respect to $\widehat{H}$ to zero, which provides the solution for estimating the LS channel [3]. Which is portrayed as:

$$\boldsymbol{\widehat{H}_{LS}} = (\boldsymbol{X^H X})^{-1} \boldsymbol{X^H Y} = \boldsymbol{X^{-1} Y} \qquad \textbf{(2.8)}$$

Hence, the LS channel estimate $\widehat{H}_{LS}$ for every subcarrier, can be expressed as follows:

$$\widehat{H}_{LS}[k] = \frac{X[k]}{Y[k]} \qquad \textbf{(2.9)}$$

while the mean-SE (MSE) of the measurement of the LS channel is measured as:

$$MSE_{LS} = \frac{\sigma_z^2}{\sigma_x^2} \qquad \textbf{(2.10)}$$

2.8 Mathematical model of MMSE Channel Estimator:

As we know the LSE solution in the above Equation, $\widehat{H}_{LS} = X^{-1}Y = \widetilde{H}$. Thus, by using a weight matrix W, we can define $\widehat{H} = W\widetilde{H}$, which corresponds to the MMSE Estimation (Cho, Kim, Yang, & Kang, 2010). Looking at the figure (2.7) below the mean-SE of the c-estimate $\widehat{H}$ [3]. Which is represented as:

$$j`(\widehat{H}) = E[||e||^2] = E[||H - \widehat{H}||^2] \quad \textbf{(2.11)}$$

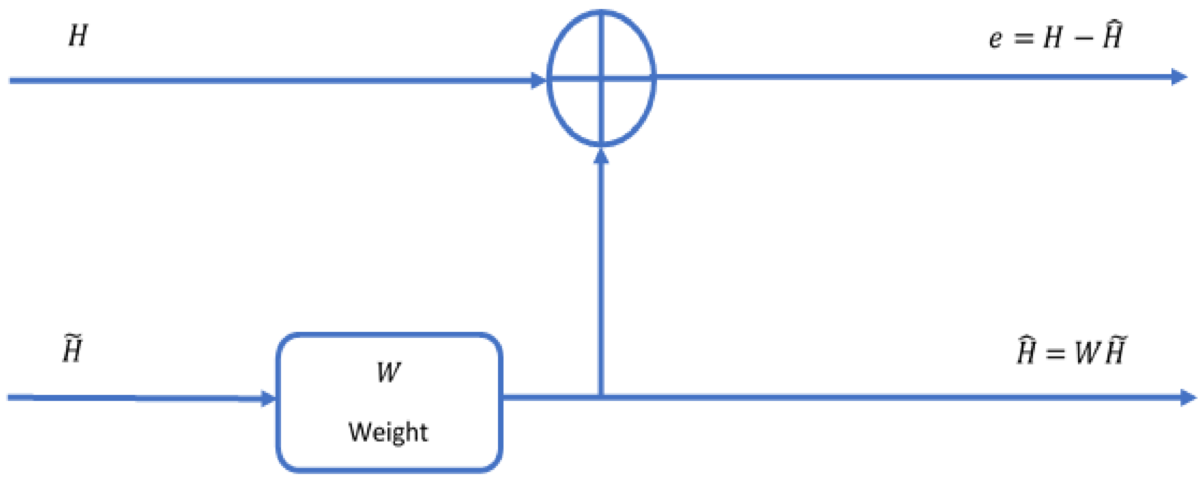


Figure 2. 7: Block Diagram for MMSE CE.

Formerly, the MMSE-CE approach is used in discoveries of an improved approximation with a linear characteristic in terms of W in such a way that the MSE in Equation (2.11) is diminished. Thus, according to the ortho-principle which states that the vector of estimation error $e = H - \widehat{H}$ is ortho to $\widetilde{H}$ (Cho, Kim, Yang, & Kang, 2010), if the equations below are fulfilled:

$$E\{e\widetilde{H}^H\} = E\{(H - \widehat{H})\widetilde{H}^H\} \quad \textbf{(2.12)}$$

$$= E\{H\widetilde{H}^H\} - WE\{\widetilde{H}\widetilde{H}^H\} \quad \textbf{(2.13)}$$

$$= R_{H\widetilde{H}} - WR_{\widetilde{H}\widetilde{H}} = 0 \quad \textbf{(2.14)}$$

Where $R_{H\widetilde{H}}$ is the matrix of cross-correlation and $R_{\widetilde{H}\widetilde{H}}$ is the auto-correlation so looking back at LS channel estimation (Cho, Kim, Yang, & Kang, 2010). which is represented as:

$$\widetilde{H} = X^{-1}Y = H + X^{-1}Z \quad \textbf{(2.15)}$$

And through solving this equation (2.15) for W we get:

$$W = R_{H\widetilde{H}} - R_{\widetilde{H}\widetilde{H}}{}^{-1} \quad \textbf{(2.16)}$$

And,

$$R_{\widetilde{H}\widetilde{H}} = E\{\widetilde{H}\widetilde{H}^{H}\} = E\{HH^{H}\} \quad \textbf{(2.17)}$$

Were,

$$R_{\widetilde{H}\widetilde{H}} = \frac{\sigma_z^2}{\sigma_x^2} I \quad \textbf{(2.18)}$$

Thus, the MMSE channel estimate is stated in following equation (2.19) as:

$$\widehat{H} = W\widetilde{H} = R_{H\widetilde{H}} R_{\widetilde{H}\widetilde{H}}{}^{-1}\widetilde{H} \quad \textbf{(2.19)}$$

2.9 EM Algorithm Based CE:

The Expectation Maximization (EM) algorithm has been commonly used in a broad number of fields, such as biology, signal processing, clinical, econometric, and sociological research, which deal with unknown characteristics influencing the outcome (Cho, Kim, Yang, & Kang, 2010). The c-estimation method based on EM is an iterative technique used to find a channel's maximum likelihood (ML) estimates. It is thus known as a semi-blind method because it can be applied when symbols are not visible or partly available for transmission (Cho, Kim, Yang, & Kang, 2010).

3. Machine Learning Channel Estimations Approaches

3.1 Introduction to Machine Learning (ML):

M-learning is an artificial intelligence technology that allows systems the ability to learn and develop automatically from experience without being directly programmed (Kim, 2017). M-learning can also be seen as the artificial intelligence branch that involves techniques or algorithms for automatically constructing data models by observation (Osinga, 2018).

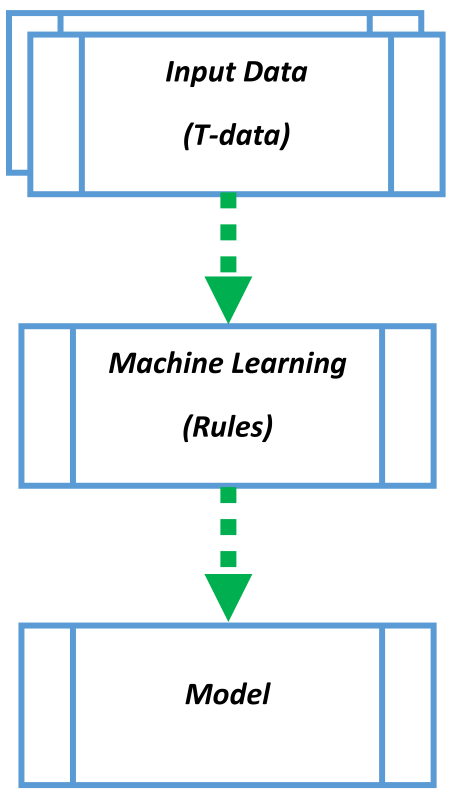


Figure 3. 1: Machine Learning Process.

According to the above block diagram machine learning process in it is simplest form consist of three stages which are, data collection and pre-processing, passing the set of prepared data through a predefined rule called as training process then generating a model from the input data and tunning it is performance to be used for future inferences.

3.2 M-Learning Types:

Four foundational methods can be categorized as machine learning (ML) algorithms: supervised learning, unsupervised learning, semi-supervised learning and reinforcement learning (Josh Patterson, 2018; Osinga, 2018).

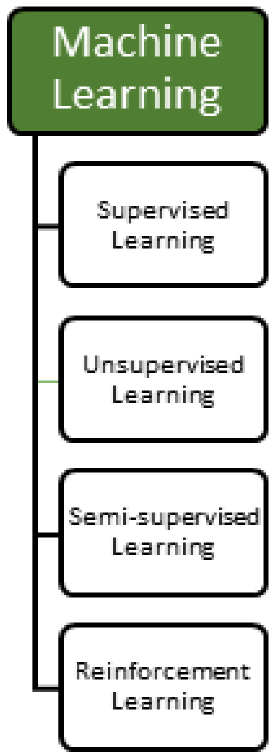


Figure 3. 2: Types of ML.

3.2.1 Supervised M-Learning:

In this method of ML, where the M-learning algorithm is fed with labeled t-data and validation data, the algorithm's input and output are both established and known to the engineer (Bell, 2015; Alpaydın, 2010).

3.2.2 Unsupervised M-Learning:

Algorithms that train on unlabeled data are used in this form of unsupervised M-learning. As the algorithm searches input data sets to look for any meaningful patterns on which it can construct a model for this data. (Bell, 2015; Kim, 2017).

3.2.3 Semi-supervised M-Learning:

This sort of M- learning requires a combination of supervised and unsupervised approaches to learning (Alpaydın, 2010). The algorithm is fed limited number training points; However, the model is able to analyze the input-data on its own and develop its own interpretation of the data collection (Alpaydın, 2010).

3.2.4 Reinforcement ML:

Reinforcement-learning is usually used to instruct a computer to finish a multi-step procedure for which rules are explicitly specified (Alpaydın, 2010).

3.2.5 Applications of Supervised Learning:

Supervised machine learning requires to train the system with labeled inputs beside desired outputs, thus supervised learning application are (Bell, 2015):

- Binary grouping, separating and classifying data into two groups.
- Multiclass classification, whereas we choose from more than two kinds of responses.
- Modeling regression, where we forecast continuous values.
- Ensembling, in which we mix several machine learning models' predictions to generate an accurate forecast.

3.2.6 Applications of Unsupervised Learning:

The unsupervised learning methodology does not require marking of training data-sets, thus to search for similarities that can be used to organize data points into subsets, then they sift through unlabeled data (Alpaydın, 2010). Many types of deep learning are unsupervised algorithms, including neural networks. For the following tasks, unsupervised ML algorithms are fine to use (Bell, 2015):

- Clustering. Splitting the data set into groups based on similarity.
- Anomaly detection. Identifying unusual data points in a data set.
- Association mining. Identifying sets of items in a data set that frequently occur together.
- Dimensionality Reduction. Reducing the number of variables in a data set.

3.3 What is Deep Leaning:

Deep learning (DL) is an approach to M-learning that mimics the functioning of the brain structure and operation of the human intelligence, which is also termed as artificial-NN (Andreas

C & Guido, 2017). D-learning methods are capable of learning from both unstructured and unlabeled data without human oversight (Osinga, 2018). One valuable description specifies that deep learning deals with a N-network with higher than one layer, the following are some of the surfaces in this development of N- networks:

- Has more neurons than previous networks.
- More complex ways of connecting layers/neurons in NNs.
- Explosion in the amount of computing power available to train.
- Automatic feature extraction.

3.3.1 Deep Learning Working Principle:

Neural network architectures are used for most deep learning approaches, which is why D-learning models are sometimes referred to as deep neural networks (DNNs) (Andreas C & Guido, 2017). In general, a N-network consists of a set of units or connected nodes (Osinga, 2018). These nodes we call as neurons. The biological neurons in our brain are modelled roughly by these artificial neurons. In overall, the expression deep refers to the sum of hidden layers in the N-network as shown below in figure (3.3):

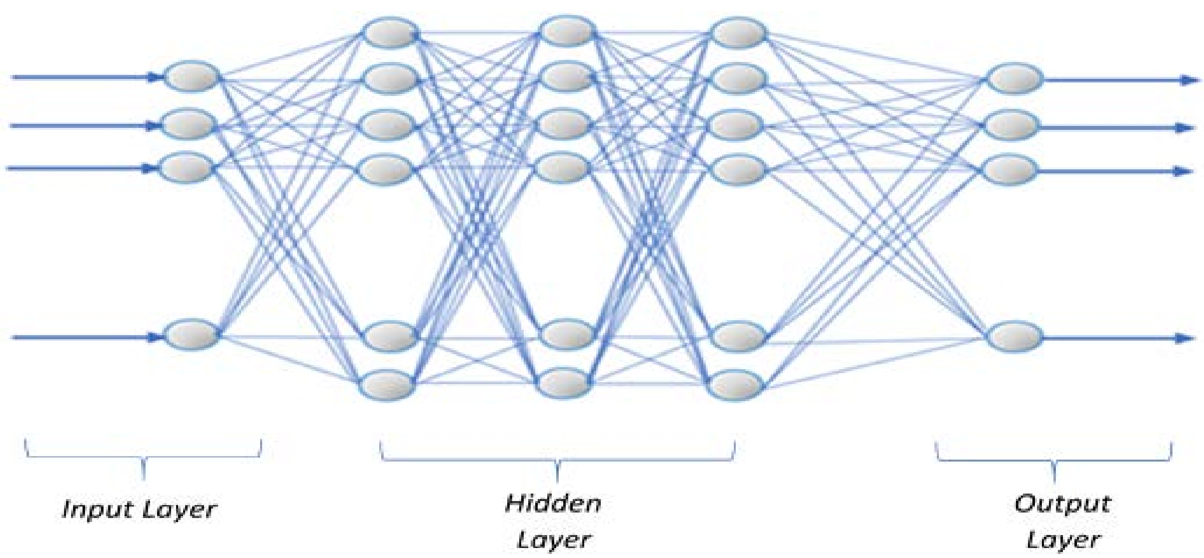


Figure 3. 3: Structure of Neural Network.

D-learning methods are programmed by using big sets of labeled data and N-network constructions that are able learn features directly from the data without the need for manual feature extraction (Gibson & A, 2017; Andreas C & Guido, 2017). Thus, by finding and discovering structures in the data they experience, D-learning networks learn a sophisticated model. The networks may generate several levels of abstraction to represent the data by creating conceptual models that consist of several processing layers (Kim, 2017; Andreas C & Guido, 2017).

The D-Learning Network architecture consists of the following components in its simplest form:

- Number of neurons.
- Number of layers.
- Types of connections between layers.

3.3.2 Concept of a Neuron:

The neuron is the essential computational block of a Deep Learning Network. The neuron has a set of input features x_n and each feature x_n is multiplied with a weight w_n (Gibson & A, 2017). Then the multiplied weights are summed up according to:

$$y = \sum_{n=1}^{N} x_n w_n + b \tag{3.1}$$

Where b is well-defined as the weight bias, the purpose of the bias weight is to be able to represent the output of the neuron in a perhaps broader range compared to the input domain. The output of the neuron z is finally given by $z = g(y)$, where $g(y)$ correspond to the activation function. The purpose of the activation is to perform a non-linear mapping of the weighted summation to the output so that it can be decided if the neuron was activated or not (Kim, 2017; Josh Patterson, 2018).

3.4 Activation Functions:

Activation Functions used in deep learning can be of many types but considering this thesis approach we will be dealing with one or more of the following types of activation functions throughout all the design process (Bell, 2015).

3.4.1 Sigmoid Function:

There are many available activation functions used for deep learning networks, here three classical activation functions are presented. The first activation function is the sigmoid function and as we know the sigmoid function has a range between 0 and 1 and is easy to apply (Gibson & A, 2017; Bell, 2015):

$$\sigma(x) = \frac{1}{1+e^{x}} \qquad \textbf{(3.2)}$$

The following figure (3.4) shows the sigmoid activation function graphically:

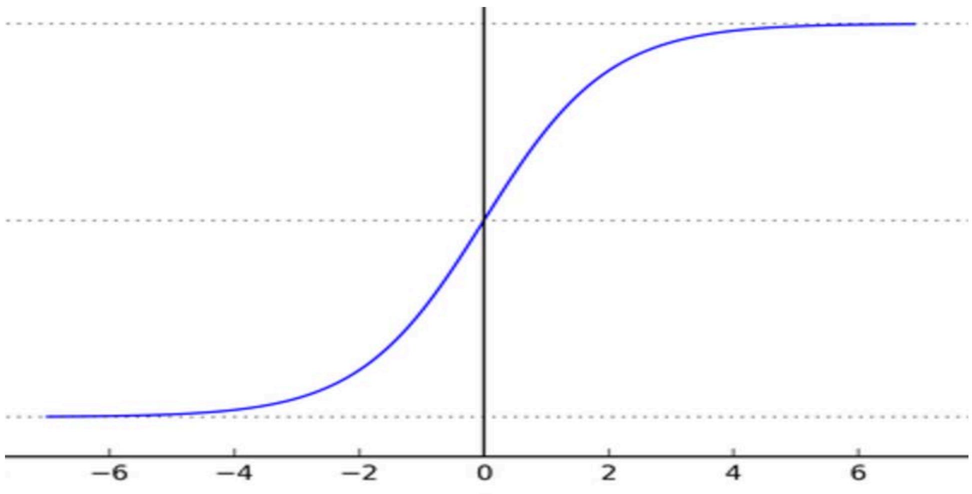


Figure 3. 4: Sigmoid Function.

3.4.2 Hyperbolic Tangent Function:

The second known activation function is the hyperbolic tangent function. Where this function is zero centered and it is derivative is not as narrow as the derivative of the sigmoid function. but the main drawback of the hyperbolic tangent function it suffers from the problem of vanishing gradient (Theobald, 2017). Which is expressed mathematically as:

$$y(x) = tanh(x) \qquad \textbf{(3.3)}$$

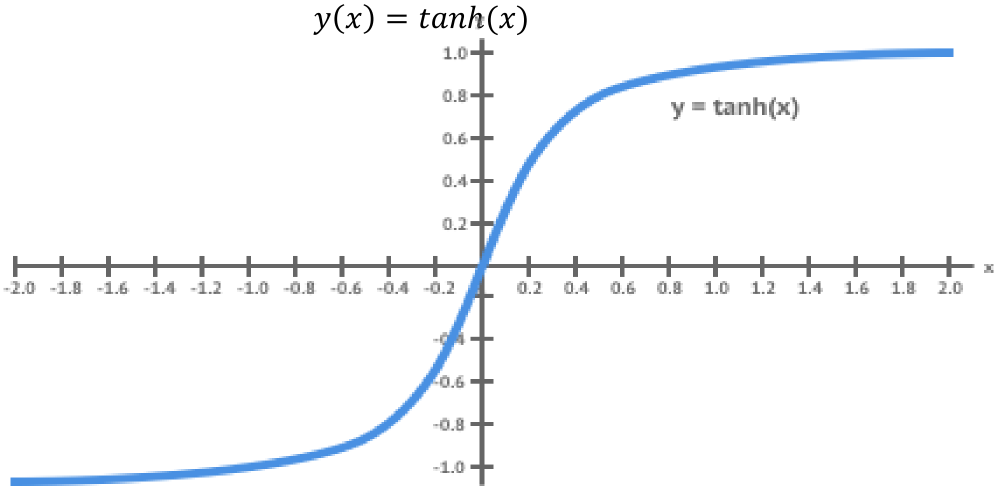


Figure 3. 5: Hyperbolic Tangent Function.

3.4.3 Rectified Linear Unit Function:

This function is utilized to obtain the output of a neural network as true / false and the Rectified linear unit function it does not suffer from the vanishing gradient problem compared to the hyperbolic tangent function (Kim, 2017). Thus, this function it is expressed mathematically as:

$$f(x) = max(0\,, x) \tag{3.4}$$

Or it is expressed as:

$$f(x) = \begin{cases} x, & if \;\; x > 0 \\ 0, & otherwise \end{cases} \tag{3.5}$$

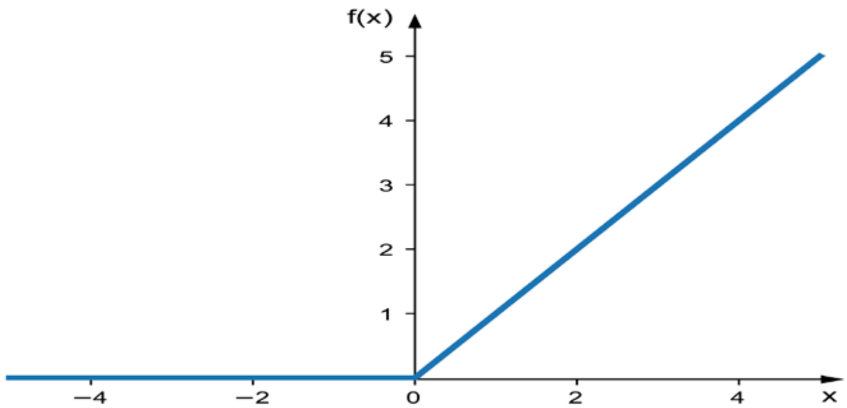


Figure 3. 6: RELU Function.

3.5 Introduction Machine Learning Approaches for Channel Estimations:

As we know cellular communication systems encounter different types of noises and impairments, thus such behaviors cannot be well estimated by traditional estimation methods like training symbol-based approaches such as LS Estimator and MMSE. The main downside of the LSE C-estimation is deserting the presence of noise in the estimation process itself. Moreover, MMSE channel estimation approach provides better performance compare to LS approach, but at high computational complexity plus it is only useful in some situations. Lately, Deep learning-based approaches are used to find fine types of imperfections in real-world cellular communication systems with advantages of low computational complexity, making DL approaches as very capable methods, particularly in channel estimation (Aggarwal Charu, 2018).

3.6 DL Approaches Used in Channel Estimations Are:

When it comes to using deep learning approaches for communication systems channel estimation there a lot of deep learning approaches that can be used to achieve such task by using wide ranges of methods and techniques so in the following few headings, we will list some of the deep learning techniques use I channel estimation area.

3.6.1 Auto Encoder Approach:

Autoencoders (AEs) are classified as an unsupervised artificial neural network algorithm in which the system leverages the neural networks with the aim of representation learning and predicting some behaviors. Autoencoder is classically used in the case of dimensionality reduction problems. Lately, autoencoders are also used as a tool for denoising of signals. By training the autoencoder researchers aim at removing the noise and focus on important parameters of the input signal that is called as latent vectors (Ye, Li, & Juang, 2018).

3.6.2 Generative Adversarial Approach:

In short, Generative-AN (GANs) are a generative simulation approach utilizing D-learning techniques, such as coevolutionary N-networks (CNNs) (Aggarwal Charu, 2018). Generative casting is classified as an unsupervised M-learning activity that involves automatically while determining and learning the regularities or patterns of an input data in such a way that new examples can be created or developed by the model that might have been plausibly taken from the original dataset (Aggarwal Charu, 2018).

3.6.3 Convolutional Neural Network Approach:

Convo-neural network (CNN) is a type of D-learning algorithm that can take in input data, assign significant weights to different aspects of the data, and be able to distinguish between them from each other (sorting) (Murphy, 2012). Compared to other classification techniques, the pre-processing required in a Convo-NN is much lower, while in primitive methods filters are hand-engineered, with sufficient training, Convo-NN has the ability to learn these filters or features of the inputs (Kim, 2017).

3.6.4 Deep Neural Network Approach:

Deep learning is a form of ML that models the patterns of data as complex networks with multiple layers (Andreas C & Guido, 2017). Since deep learning is the most common way to model a problem, it has the potential to solve problematic difficulties such as computer vision and processing of natural language that have overtaken and outstripped conventional programming and other techniques of machine learning (Josh Patterson, 2018; Cho, Kim, Yang, & Kang, 2010). Not only can D-learning produce useful outcomes where other techniques straggles, but it can also construct more precise models than other techniques, and can reduce the time needed to construct a useful model (Aggarwal Charu, 2018) (Andreas C & Guido, 2017). Training D-learning models, however, requires a great amount of computing power, the difficulty of interpreting D- learning models are another drawback to deep learning (Aggarwal Charu, 2018).

3.7 Advantages of Machine Learning Approaches:

The prime advantages of using machine learning models base channel estimator in a cellular communication system are:

- Faster and real time predictions can be attained easily.
- Continuous improvement can be established rapidly.
- Supplying accurate results that can be verified.
- You can use specialized hardware or make use of available hardware efficiently.
- Abundant resources of input data.
- High efficiency.

3.8 Proposed Model Block Diagram:

We propose the following block diagram of a deep learning-based algorithm for channel estimation which we will explain in details in later chapters as follows:

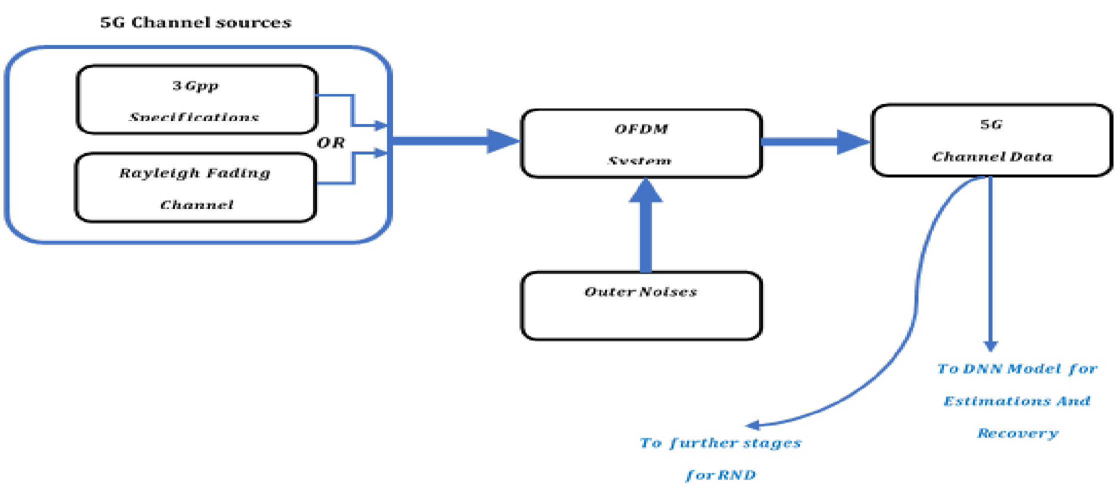


Figure 3. 7: Proposed Block Diagram.

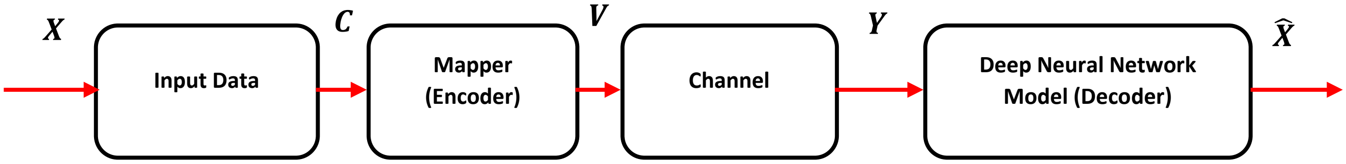


Figure 3. 8: Proposed Architectural Block Diagram of a Deep-NN Decoder.

DNN's architecture is seen in figure (3.8). We assume that the length N of information bits (X). at the transmitter side of our 5G-system above, and X is modulated to a binary code-word (C) of length L and passed through to the next stage of the process where the codeword C are transformed to a symbol vector (V) through the modulation scheme 16QAM. Then the 16QAM, at the receiver, the received data vector Y is expressed mathematically as:

$$Y = V + Noise \tag{3.6}$$

Then the received data X is estimated and represented as $\hat{\boldsymbol{X}}$ by decoded it from Y with the assistance of the deep neural network model that we have designed with the consideration that the noised added by the channel is assumed to be of zero and variance σ^2.

3.9 Why Choosing to Use Machine Learning for Channel Estimations:

Current developments in Machine Learning and especially Deep Learning implementations and theories have catalyzed noteworthy research among electronics and communications engineering researchers' community. And that is due to numerous reasons such as:

- Deep neural network encoders and decoders are more accurate compared to the available traditional methods used for channel estimations.
- CE based on deep learning models have an amazing performance upgradability and adjustability.
- CE based on deep learning models have advanced analysis capabilities and more dynamic.
- CE based on deep learning models can leverage the available hardware and utilize the processing power efficiently.
- CE based on deep learning models can process huge number of inputs swiftly without any performance degradations under many operating conditions.

4. Model Requirements and Design Procedures

4.1 Model Specification:

Our aim is to write a code to implement channel estimation using LSTM method efficiently, next validate the proposed method by using the necessary standard means. Where the simulation situations enable examination of the proposed channel estimation model performance against other traditional CE methods performances (ETSI, 2018). By taking into consideration the erroneous bit-rate and SN-ratio as the chief constraints to evaluate the estimators' effectiveness, our simulation layouts are on based the following system parameters listed in the table (4.1) below:

Table 4. 1: Model Specification.

Parameters	Specifications	Comments
Number of Users	>1	Variable
Number of Subcarriers	64	16, 32, 64, 128
Number of Pilots	64	16, 32, 64, 128
Number of Pilots Symbols	1	2, 4
Length of CP	16	16, 32, 64
Number of Path	20	Variable
Number of Data Symbols	1	Variable
Number of OFDM Symbols	2	-
Number of Classes	16	Variable
Modulation Type	16QAM	QPSK,16QAM, 64QAM, etc.
Number of Packets Per Mod-Sam	256x1e1	Variable
SNR	40	10, 20, 30, 40
5G-Channel	3GPP	Rayleigh can be used
Number of Antennas	64	Depend on the Application
Frequency	FR1	FR2 can be used
Data Rates	> 1 Gbps	Up to 10 Gbps

4.2 Data Generation:

According to the listed above specification and requirements we begin the process of designing our channel estimation model by firstly, implementing the foundational system to generate the required 5G data and secondly, we used the generated data too train the proposed model and recover the user data as accurately as possible. As we know 5G signals can have many types of weave forms but the main type that this thesis considers and use for development is Cyclic prefix-OFDM wave form which is given by the following equation as:

$$OFDM[k] = \sum_{n`=0}^{N+1} d_n e^{j2\pi k\frac{n}{N}} \tag{4.1}$$

Where N refers to the total number of sub-carriers, d_n is data symbols carried by each individual n subcarrier and k is the k^{th} OFDM data symbol, the process of 5G data generation is shown in the following chart:

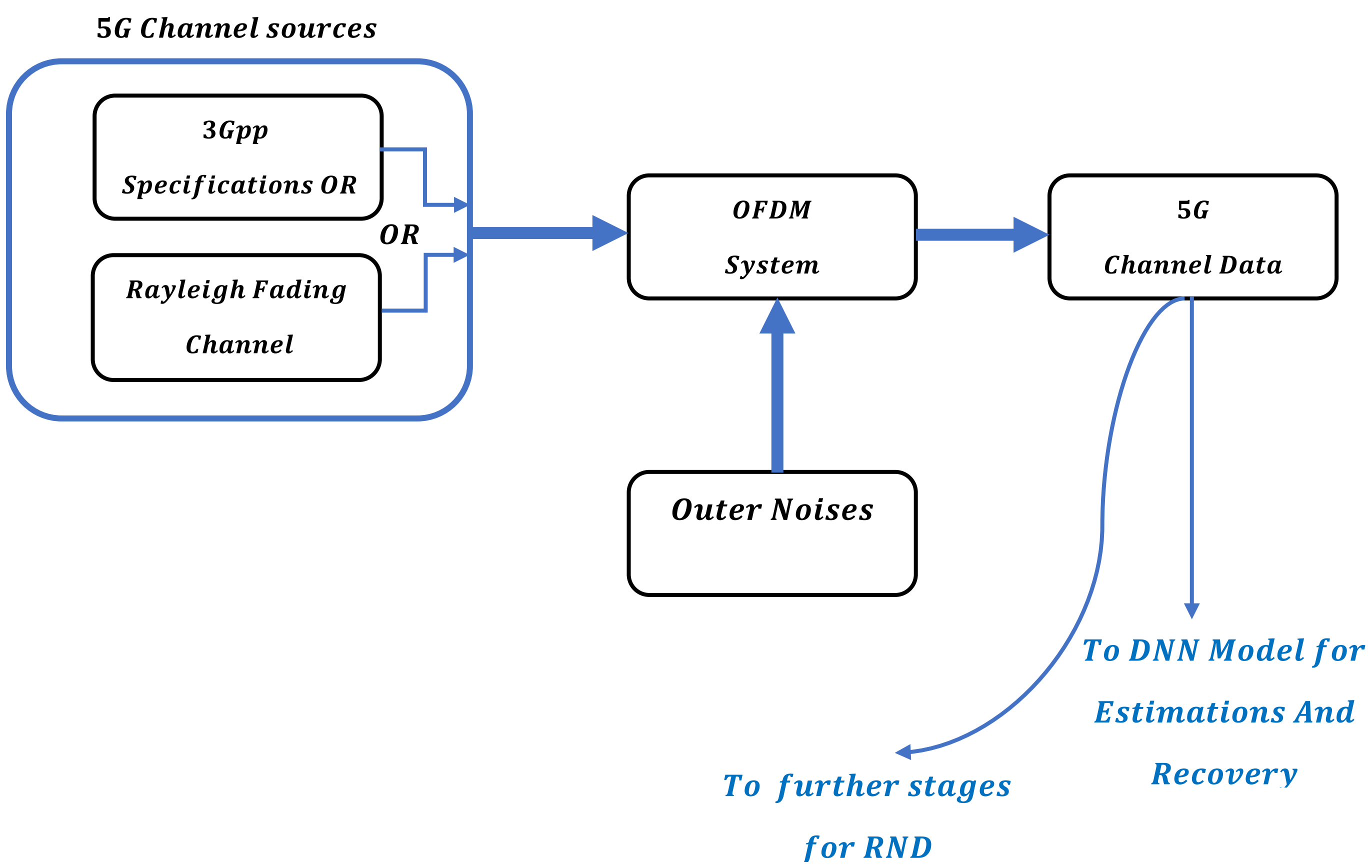


Figure 4. 1: 5G-Data Generation Roadmap.

4.3 3GPP Specifications for 5G Channel Generation:

5G uses multi frequency ranges in different frequency bands which called as freq-range one *(F-R1)* that is underneath 7.125 GHz and freq-range two (*F-R2)* which expand beyond 24.250, These both ranges are termed as 5G-New Radio (ETSI, 2018; Electronics-notes, 2020).

Table 4. 2: 5G-NR (FR1 & FR2 Ranges).

Freq-range Description	Freq-range in GHz
F-R1	4.10 – 7.125
F-R2	24.250 – 52.600

The following table (4.3) shown below reviews the signal characteristics and utilization of ranges inside (*FR1)* and (*FR2)* according to their use on each frequency bands (Electronics-notes, 2020):

Table 1. 2: 5G-NR (FR1 & FR2 Utilizations).

5G NR Parameters	FR1	FR2
Bandwidth options per carrier	5MHz-10MHz-15MHz-20 MHz-25MHz, 30MHz-40MHz-50MHz-60MHz, 70MHz, 80MHz-90MHz-100MHz	50MHz, 100MHz, 200MHz, 400MHz
Sub-Carriers' separation	15KHz, 30KHz, 60KHz	60KHz, 120KHz, 240KHz
Max-Subcarriers number	3300 (FFT 4096)	
Carrier-Collection	≥16 SCs	
Modulation schemes	QPSK, 16QAM, 64QAM, 256QAM, uplink also allows π/2-BPSK (only for DFT-s-OFDM).	
Radio frame length	10ms	
Sub-frame Period	1ms	
Type of duplexing	TDD & FDD	TDD
MIMO scheme	Max. of 2 codewords mapped to Max downlink of 8-layers Max. uplink of 4-Layers in.	

According to 3GPP ("*3GPP TS 38.300 version 15.3.1 Release 15"*), The conventional-OFDM using a cyclic prefix is used to generate the downlink transmission waveform (ETSI, 2018). The uplink transmission waveform is a normal OFDM using a cyclic prefix with a DFT spreading transform precoding feature that can be disabled or allowed (ETSI, 2018). Where sub-carrier spacing $\Delta f = 2^{\mu} x\ 15\ KHz$ where $\mu = 0,1,2,3, \ldots.$ for some channels (ETSI, 2018).

Table 4. 3: Supported Transmission Numerologies.

$\boldsymbol{\mu}$	$\boldsymbol{\Delta f = 2^{\mu} x\ 15\ KHz}$	**Cyclic prefix**
0	15	Normal
1	30	Normal
2	60	Normal, Extended
3	120	Normal
4	240	Normal

4.4 Concept of Rayleigh Fading Channel:

The Rayleigh fading channel is a mathematical model for the condition of non-line sight situation as it uses a statistical approach to evaluate electromagnetic wave propagation (Volker, 2006), The Rayleigh fading channel is perfectly suited for conditions where vast quantities of signal paths and reflections occur (Cho, Kim, Yang, & Kang, 2010) (Lathi & Ding, 2010), Typical conditions involve wireless networks where a significant amount of building reflections exist (Bullock Scott, 2017), and other objects are present which cause the transmitted signal to arrive at the receiver from many different paths and such paths can be shown as in figure(4.2) below:

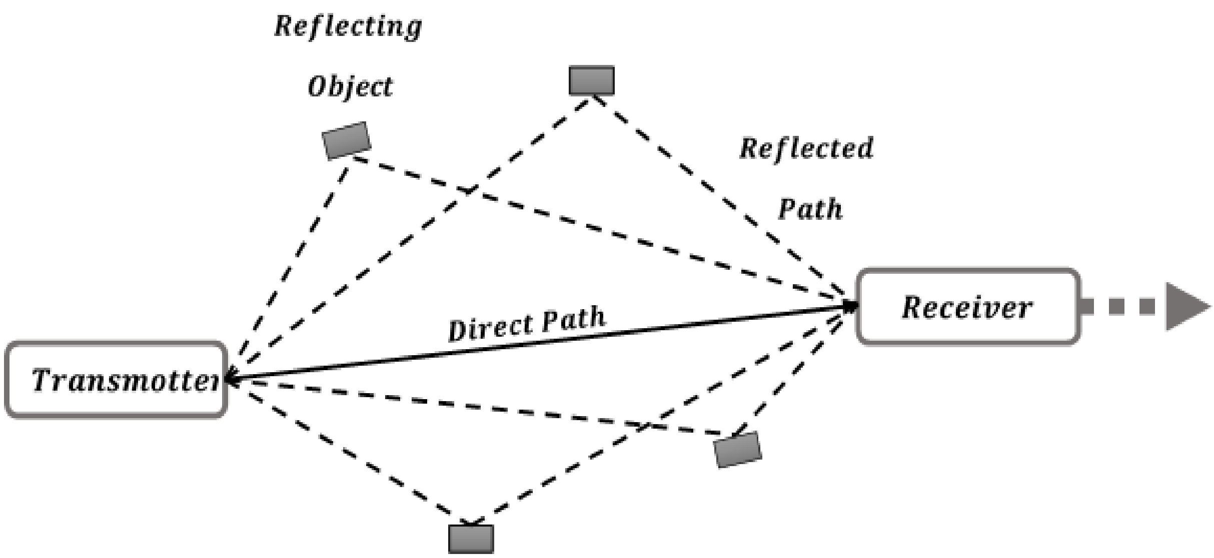


Figure 4. 2: Multi Path Reflection Suitable for Rayleigh Model.

The ultimate signal is a combination of all the signals that have reached the receiver via the multitude of different routes that are available on the transmitting route after the emitted signals enter the receiver, while these signals will sum up together, the signal phase being the important element controlling the summation of the signals on the side of the receiver (Volker, 2006). And depending on the way these signals sum up; the frequency of the signal can contrast. They would all sum up together if they were all in phase with each other. This is not necessarily the case, however, since some signals will be in phase and others out of phase, such others will also appear to contribute to the total signal, as these others will be subtracted from the total signal (Volker, 2006).

As we know, there are L paths between the transmitter and the receiver, so the response of the channel g is the sum of signals mathematically over these paths and given through:

$$g = \sum_{i=1}^{L} \sqrt{\alpha_i}\ e^{-j2\pi(\frac{d_i - d}{\lambda})} \quad \textbf{(4.2)}$$

Where:

$$\alpha_i \rightarrow is\ the\ channel\ gain\ of\ the\ i^{th}\ propagation\ path.$$

$$e^{-j2\pi(\frac{d_i - d}{\lambda})} \rightarrow is\ the\ pahse\ shift\ .$$

When L is large enough it makes good sense to use statistical models for the channel hence the channel gains will be random distributed and the phase shift will be evenly distributed between 0 and 2π because the propagation distance is larger than the wavelength, Considering the paths L are independent and identically distributed random variables so by taking into account the central limit theorem for summing lots of random vars and we will have a gaussian distribution channel response with identically distributed rand-variables thus the channel response g is expressed as:

$$g \sim N_c(0, \beta) \quad \textbf{(4.3)}$$

Where:

$g \rightarrow$ $is\ a\ complex\ gaussian$ channel response.

$$0 \rightarrow\ means\ zero\ mean.$$

$$\beta \rightarrow\ is\ the\ varianc.$$

The model in equation (4.3) above is called as Rayleigh fading model because the $|g|$ has a Rayleigh distribution where the term fading is used to signify a large variation in the quality of the channel. Now for our system consider we have a receiver with an array of antennas which receive the signals coming from multi paths due to the reflecting objects in the transmission route as shown below in figure (4.3):

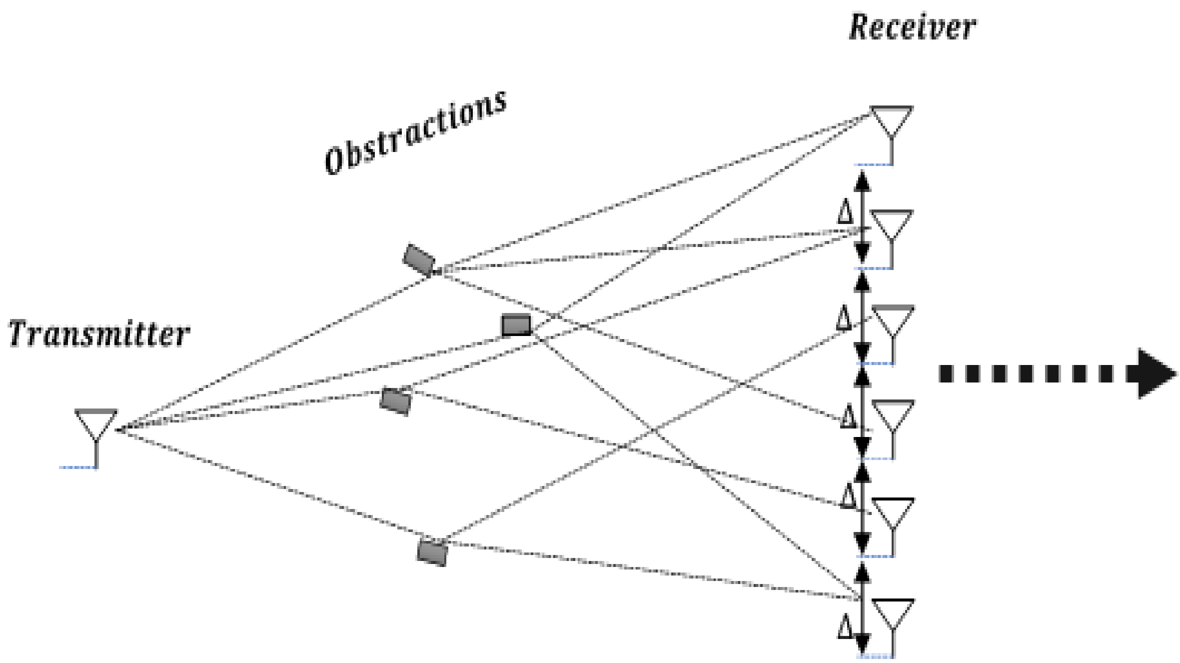


Figure 4. 3: Rayleigh Model for Practical Multi Path Channels Signals.

To ensure the received signals are independent and identically distributed where Rayleigh fading model can be used to model the above multi paths received at signals by an array of antenna the antenna spacing must be $\frac{\lambda}{2}$ and this show why the half wavelength antenna spacing is very important in cellular communication systems (PENTTINEN, 2015).

4.5 Channel Impairments:

In cellular communication system, the signal is sent over the wireless, where the wireless channel tends to deteriorate the quality of the carried signal, and the wireless channel characteristics causes signal to degrade (Lathi & Ding, 2010; Roger & Freeman, 2006). Thus, the characteristics of the channel degrading the transmitted signal quality is called as an impairment which can be such as fading, noise, path loss and so on, here we are concerned with fading phenomena in wireless communication systems which can be classified as shown in figure (4.4).

4.5.1 Large Scale Fading:

Because of barriers between the transmitter and receiver, large-scale fading refers to the attenuation of signal power, which involve attenuation and signal variations as the signal is traveling over a long distance-*Km* and signals are also shielded (Sklar, 2001). Types of Large-scale fading are:

Path Loss:

This Phenomena refers to the weakening when a signal is transmitted over great distances (Sklar, 2001), as the radio wave spread out through the channel as the distance increases as such signals they propagate, thus the energy per unit region continues to decrease when there is a type of fundamental loss that is independent of the transmitter type and medium (K, 2018; Sklar, 2001).

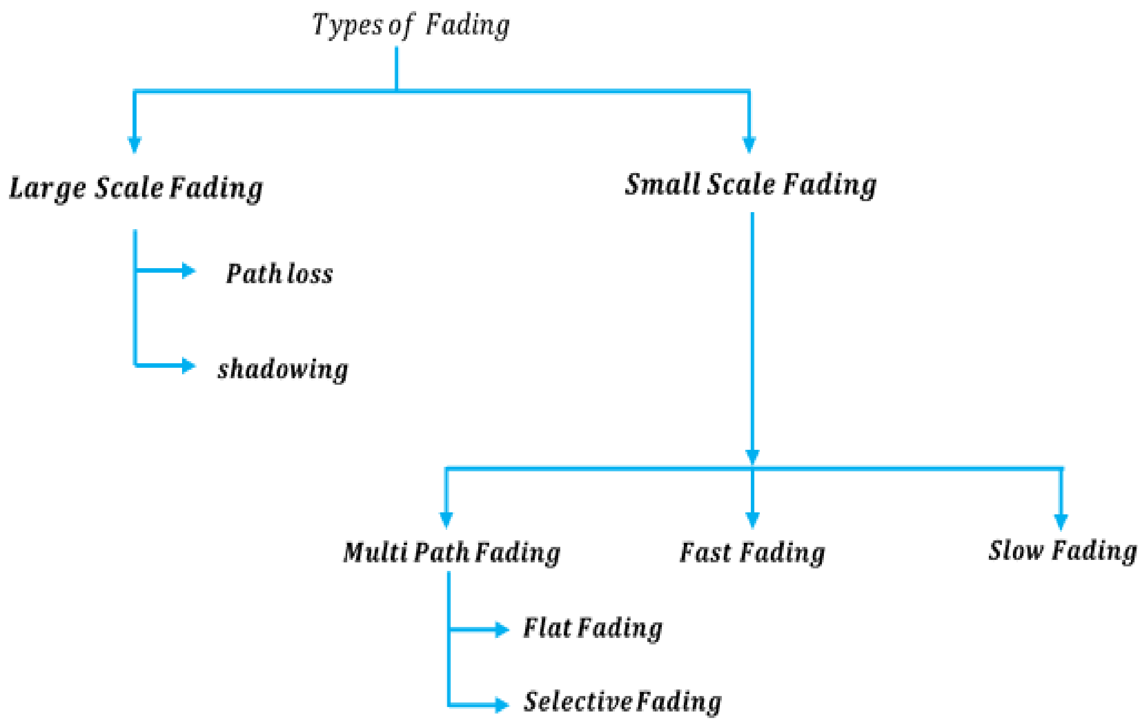


Figure 4. 4: Types of Wireless Channel Impairments.

Shadowing:

Shadowing is used represents to the lack of signal strength due to barriers such as tree, cars and other obstacles along the direction of propagation, while losses due shadowing often depends on the frequency of the EM wave (Schiller, 2003). EM Waves will pass through different materials, as we know, but at the expense of power loss, which cause an attenuation. The losses are depending on the surface type and the signal frequency (K, 2018; Roger & Freeman, 2006; Schiller, 2003).

Small Scale Fading:

The variations in signal intensity and phase over a short distance and a small period of time are represented by small scale fading, it is also referred to as Rayleigh Fading as well (Sklar, 2001). Small Scale Fading impacts and over-affects nearly all modes of wireless networking in order to improve performance and reduce errors we use some known mechanisms (Sklar, 2001). Small-scale fading are:

Fast Fading:

Fast fading happens largely due to surface reflection and transmitter or receiver movement (K, 2018; Sklar, 2001). linear-deformities in the shape of the baseband signal and creates inter-sym Interference (ISI) are caused by F-fading (Sklar, 2001).

4.5.2 Slow Fading:

Slow fading is largely due to shadowing, where the sight line of a cellular comm-system is obstructed by large buildings or spatial structures, the gradual fading results in a drop in the SN-ratio that can be resolved using error correction methods and receiver diversity strategies (K, 2018).

4.5.3 Multipath Fading:

Multi path fading happens as a signal enters the Rx-receiver from different directions, indicating that for certain reflective objects and as a function of direct line of sight transmission, the received signal is received (Iniewski, 2008). Multipath fading can attack all bands of frequencies, from microwave to low frequency and beyond, as it affects both the signal amplitude and phase, causing phase distortions and ISI distortions (Rodger E & William H, 2015). Types of multi path fading are:

Flat Fading:

Both frequency components are influenced almost evenly by flat fading process whereas flat multipath fading produces a fluctuation of the amplitude over a span of time (Goldsmith, 2005) (Rodger E & William H, 2015).

Selective Fading:

Freq-selective fading is also called as Selective Frequency Fading denotes the process of multipath fading occurring for only selected freq-constituent of the transmitted data-signals suffers from such effects (Goldsmith, 2005; Schiller, 2003). By using modulation techniques such as OFDM, which stretches the data through the frequency components of the signal to minimize data leakage and hence selec-frequency fading can be resolved (Rodger E & William H, 2015; Lyu, Z, J, Q, & Z., 2018).

4.6 5G - Data Generation System Coding:

We start the process of implement our proposed system by specifying the OFDM system parameters as follows:

```
nSC = 64;                           % No. of subcarriers
nPilo = 64;                         % No. of pilot subcarriers
Pilo_Spc = nSC/nPilo;               % Pilot Spacing
nPiloSym = 1;                       % No. of Pilot Symbols
nDSym = 1;                          % No. of Data Symbols
nOFDMAsym = nPiloSym + nDSym;       % No. of OFDMA Symbols
lenCP = 16;                         % Length of the cyclic prefix
```

For the modulation process we have used 64 subcarriers to carry the user's data and those 64 subcarriers are modulated by using 16 modulation constellations symbols, also for the correct data recovery we use the pilot symbols and place them at specific predefined intervals throughout the transmitted frames.

```
%% OFDMA system parameters
[nSC, nPilo, Pilo_Spc, nPiloSym, nDSym, nOFDMAsym] = OFDMAsys_params ();
```

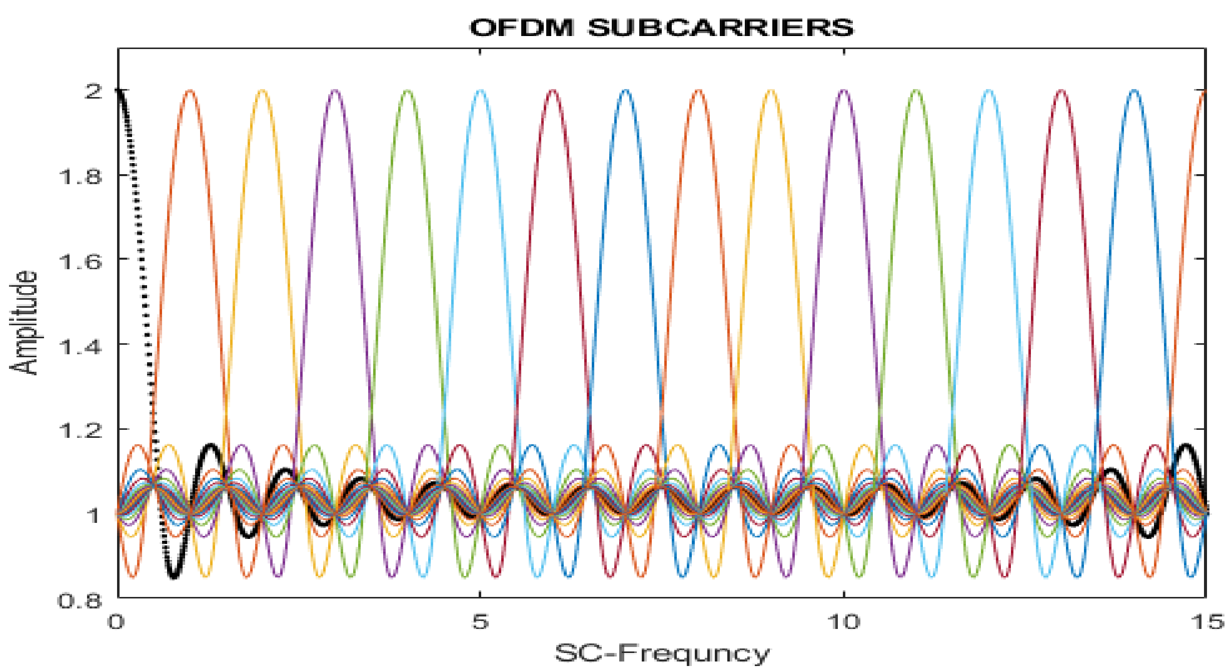


Figure 4. 5: OFDM Subcarriers.

Then the design process moves to the next step by defining the modulation scheme as 16-QAM the data is loaded into the subcarriers by using 16 classes or constellation symbols, these modulating symbols and the subcarriers are shown graphically as in figure (4.6) below:

```
%% QPSK, 16QAM, 32QAM, 64QAM, 256QAM modulation
[M, x, Label, moduSig, Ncls] = OFDMA_modConst ();
```

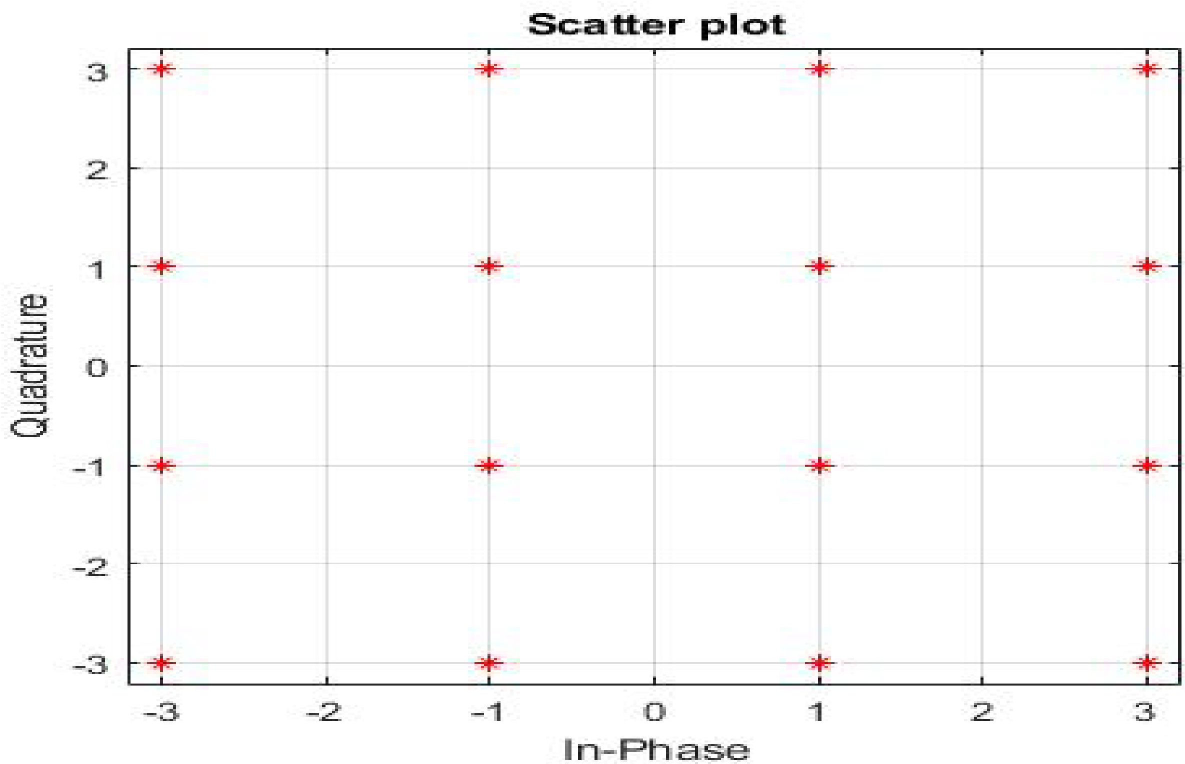


Figure 4. 6: OFDM Modulating Symbols.

Next the design procedure progress to the subsequent phase by specifying the target 5G channel through the use of Rayleigh fading model which represent the 5G channel model as described by the 3GPP documentation (3GPP TR38.901 channel model) as follows (ETSI, 2018):

```
%% 5G channel generation
h = 1/sqrt(2)/sqrt(nPath)*complex(randn(nPath,1), randn(nPath, 1));
H = fft(h, nSC, 1);
```

Then the proposal procedure progress to the following phase by specifying the noise level and the data set size for the proposed system as follows:

```
%% Signal to Noise Ratios calculation
enrgSdB = 40;
EsN = 10.^(enrgSdB./10);
noiSdB = 1./EsN;
noiVariance = noiSdB./2;
```

```
%% Size of dataset to be defined
nPackPerCls = 256*1e1;                  % Number of packets per modulation symbol
```

The succeeding stage of generating 5G data end with wrapping up all the above steps together by modulating the user data through the use of the constellation symbols and at the mean time the constellation symbols are use as the labels for the transmitted data because all the transmitted symbols are converted into one out of the 16 constellation symbols, after that we used the modulated data to generate the transmitted frames and received frames as follows:

```
%% OFDMA Pilot symbol insertion between the Data Symbols
PiSym = 1/sqrt(2)*complex(sign(rand(nPiloSym, nSC, nPackPerCls)-0.5), sign(rand(nPiloSym, nSC,
nPackPerCls)-0.5));
PiSym(1 : Pilo_Spc : end) = PiloPOSAll
%% OFDM data symbol
dSym = 1/sqrt(2)*complex(sign(rand(nDSym, nSC, nPackPerCls)-0.5), sign(rand(nDSym, nSC,
nPackPerCls)-0.5));
CurrSym = 1/sqrt(2)*moduSig(i)*ones(nDSym,1, nPackPerCls);
dSym(:, SCid, :) = CurrSym
%% OFDMA frames transmission and frames Receptions
TxdFrames = [PiSym;dSym];
RxdFrames = trxOFDMAsig(TxdFrames, lenCP, h, noiVariance);
```

Then after the process of loading the data into the subcarriers and interleaving the resultant data with the pilot symbols at a predefined interval we label the transmitted symbols and extract the necessary features vectors form which we collect our 5G training data as follows:

```
%% Training data collection
dLabel = Label(i)*ones(1, nPackPerCls);             % Data label for the current sC
[Fea, label] = feaLExtraction(real(RxdFrames), imag(RxdFrames), dLabel, i);
FeaVec = mat2cell(Fea,size(Fea, 1),ones(1, size(Fea, 2)));
X` = [X FeaVec];
Y` = [Y label];
```

Here X`, Y` are the target training data which we will passed to the designed DNN model to train it and generate a precise model which can be used for future predictions.

Finally, the progression of 5G data generation is concluded with dividing the collected data into training data and validation data in ratio of $2/_{10}$ where 80% of the data will be used for training and the rest 20% will be used for testing process then saving the training ad validation data as $tDATA$ and $vDATA$ as follows:

```
%% Save the training data for training the neural network
Save_tvpData ();
```

4.7 Long-Short Term Memory:

Before diving into what is LSTM lets gives a gentle overview of DNN from mathematical point of view, Mathematically, we can describe the neural-N as a distinct function that maps one type of variable to another type of variable, i.e. We map a vector to another vector for categorization problems (Gibson & A, 2017). LSTM -**"**long-short-term memory" networks are one type of NN that are selectively encoded to learn and remember or forget specific inputs. Thus, LSTM is clever sufficiently to control how long to grip onto old data, and when to recall or forget, and how to make connections between old recall with the new input (Aggarwal Charu, 2018).

4.7.1 LSTM Architecture and Working Principle:

The basic LSTM Network architecture consist of following three elementary elements which are called as gates, The LSTM architecture is shown graphically as follows: *Input Gate* - *Forget Gate* - *Output Gate* (Josh Patterson, 2018).

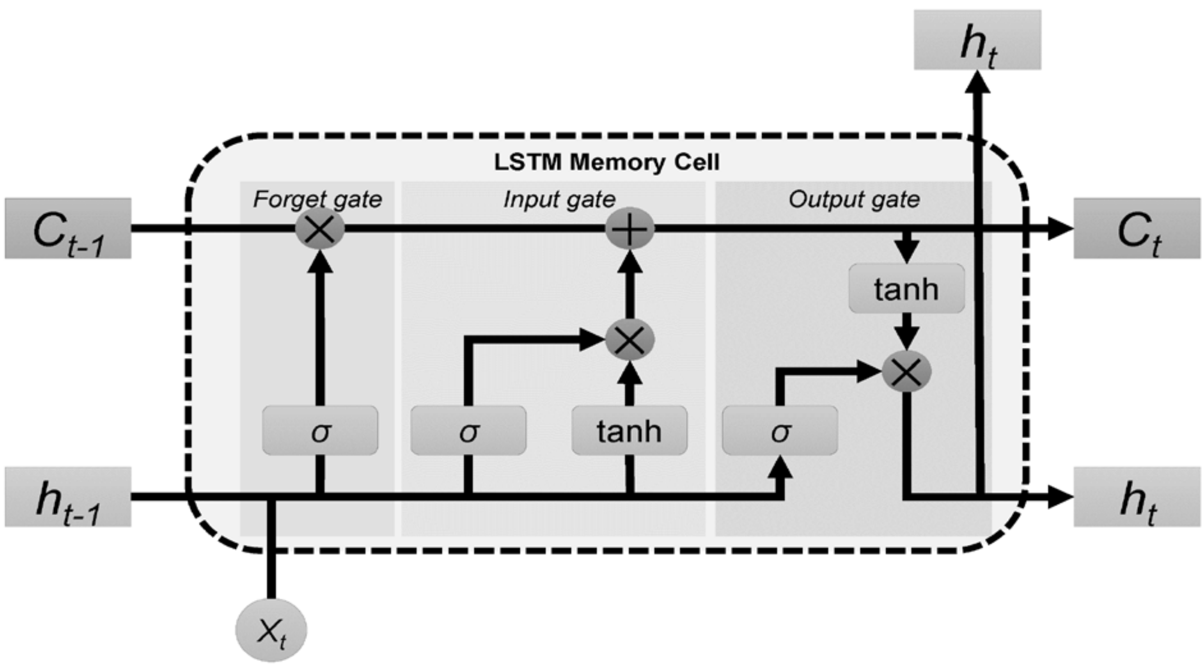


Figure 4. 7: LSTM Basic Cell Architecture.

The complete LSTM cell interconnections to achieve the desired goal is shown in the following figure (4.8) below:

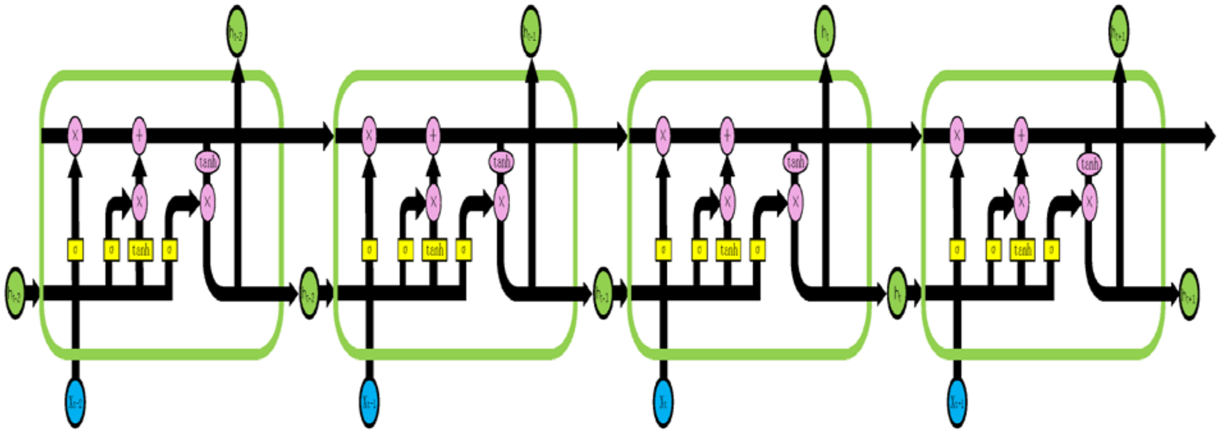


Figure 4. 8: LSTM Network Architecture.

The Prime reason to choose and used LSTM is to avoid the vanishing and exploding gradients problems associated with the classic deep neural networks which cause loss of input information when using them, also the second reason to use LSTM is as follow LSTM is suitable for time-series data (Alpaydın, 2010; Aggarwal Charu, 2018).

When using LSTM, we replace every hidden unit of a deep neural network by using one LSTM cell where each LSTM cell maintain an LSTM cell-vector state-run C_t and the next LSTM cell can decide to read from the previous cell state vector, write to it or rest it by using explicit gating mechanism called as (Aggarwal Charu, 2018):

- Input Gate.
- Forget Gate and.
- Output Gate.

The input gate determines whether to change the memory cell "$i^{(t)} = \sigma(w^i[h^{(t-1)}, x^{(t)} + b^i)$" , then the memory cell is reset to zero or not, by the forgotten gate regulate and decide if "$f^{(t)} = \sigma(w^f[h^{(t-1)}, x^{(t)} + b^f)$", Therefore the output gate regulates whether the existing cell state information is C_t if it is rendered visible or not "$o^{(t)} = \sigma(w^o[h^{(t-1)}, x^{(t)} + b^o)$" (Josh Patterson, 2018; Gibson & A, 2017).

Every one of gates have a sigmoid activation σ to constitute a smooth curve spanning from 0 to 1 and also to ensure that the remaining mode is distinguishable, noting that the vector also $\bar{C}_t$ by using tanh activation, can change the vector-cell where "$\bar{C}_t = tanh(w^c[h^{(t-1)}, x^{(t)} + b^c)$" to permit the data on the cell-state to flow longer without missing or exploding (Aggarwal Charu, 2018).

The secret/hidden state is taken by each of the gates as "$h^{(t-1)}$" in addition it also takes the current input x_t and it concatenate those vectors by applying sigmoid activations and generate $\bar{C}_t$ where a new contender value that can be added to the cell state can be formulated.

4.8 Implementation and Training Deep Learning Model:

After deciding which approach to use implementing our proposed deep learning model, we start by designing the actual model and then loading the generated validation-points and training-sets to run the model as follows:

```
%% Loading Our Generated Training Data and validation data
load('tDATA.mat');
load('vDATA.mat');
```

Next, we set our training parameters by specifying the input data size to train the model on the labels which the model will classify the data based such data to 1 out of 16 classes, quantity of Epoch, and the numeral of hidden units as follows:

```
%% Setting the DNN training parameters
InputSize = 2*nOFDMAsym*nSC;
nSC = length(Label);
MiniBatchSize = 1000;
MaxEpochs = 100;
NumHiddenUnits = 20;
```

After that we will input these training parameters to the long-STM model to start the training process through the specification of the types of layers to use in our training process as follows:

```
%% Specifying DNN layers For Subsequent Processes
Layers = [ ...
sequenceInputLayer(InputSize)
lstmLayer(NumHiddenUnits,'OutputMode','last')
fullyConnectedLayer(nSC)
softmaxLayer
classificationLayer
];
```

Subsequently we will postulate training options to the LSTM-"long-short term memory" model as follows:

```
%% Setting the DNN training options
Options = trainingOptions('adam',...
'InitialLearnRate',0.01,...
'ValidationData',{XValid,YValid}, ...
```

```
'ExecutionEnvironment','auto', ...
'GradientThreshold',1, ...
'LearnRateDropFactor',0.1,...
'MaxEpochs',MaxEpochs, ...
'MiniBatchSize',MiniBatchSize, ...
'Shuffle','every-epoch', ...
'Verbose',0,...
'Plots','training-progress');
```

Finally, we will start the training phase and save trained model which we will use it in later chapter for testing and practical use as follows:

```
%% Training The DNN
Trained_dnnModel = trainNetwork(XTrain, YTrain, Layers, Options);

%% Save the TrainedModel
save('Trained_dnnModel', 'Trained_dnnModel', 'MiniBatchSize');
```

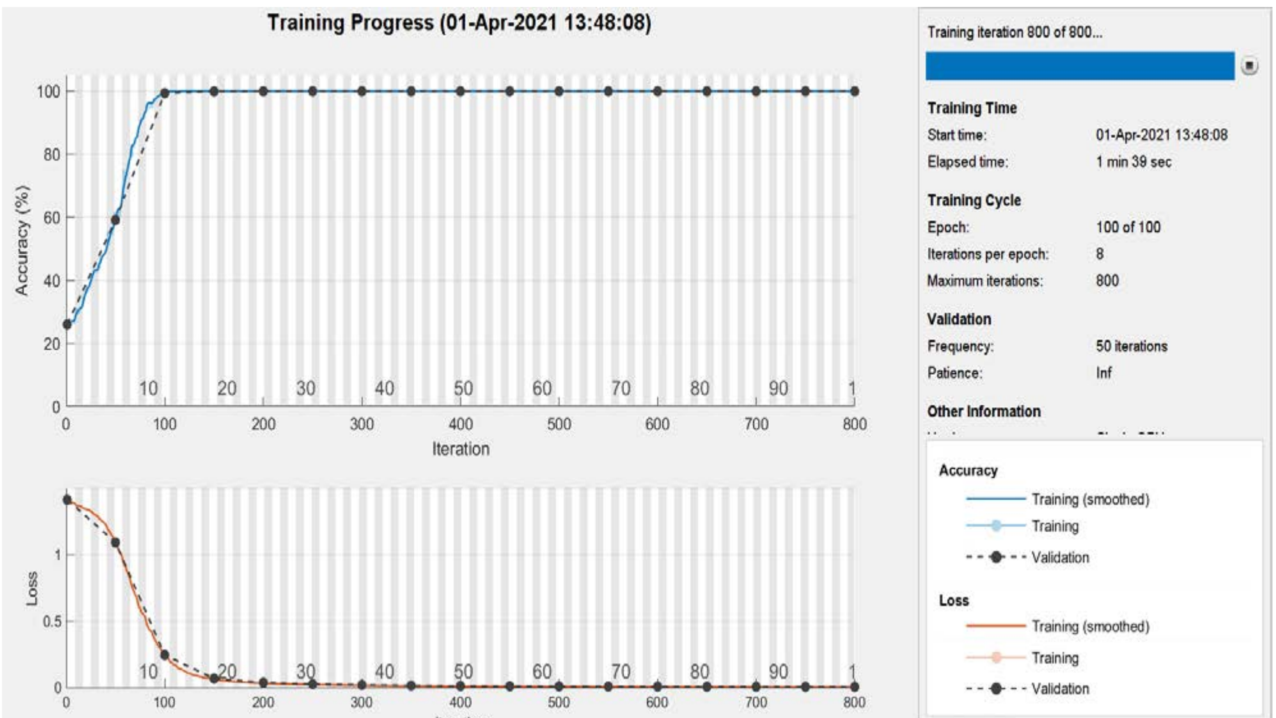


Figure 4. 9: Training Process Output.

4.9 Deep Learning Model Tunning:

Tuning our model will involve the following procedures to obtain the target results as pre stated in the design phase:

- We will change the learning rate and observe the model behavior.
- We will vary the training and validation data sets sizes and observe the model behavior.

- We will increase the noise percentage in the model input and check the model output accuracy level.
- Finally, we will test the model by using another predefined data set and tune its output accordingly.

5. Model Implementation Results and Analysis

5.1 Introduction:

This subdivision initiates the process of utilizing the designed model in chapter-4 and analyzing it is results which can be accomplished when subjecting the model to real world scenarios where we supply the model with an input data that are transmitted over long distances. Hence, the primary objectives here is divided into two parts as follows, firstly we use the proposed LSTM deep learning model to recover the transmitted data from the received data correctly then, we use the MMSE and LS for the same purpose. Secondly, we investigate the model performance under various noisy environments and measure it is accuracy in comparison to MMSE and LS accuracies in terms of BER to SNR.

5.2 OFDM System Bit Error Rate:

As we know the “orthogonal frequency division multiplexing (OFDM)” is used as one of the main elements in fifth generation cellular system (5G) thus, the OFDM system BER is calculated when we use different quadrature amplitude modulation method (QAM) with different modulation order (M-QAM). Also, when investigating the OFDM BER we consider various channel impairments as being imposed on the received data signal.

The bit error rate (BER) is important in digital telecommunication system because it illustrate how successfully the receiver is able to decipher communicated data (Bullock Scott, 2017). And it is defined as the fraction of bits with errors divided by the total amount of received bits on the receiver side, usually expressed as ten to a negative power (John W, 2018; Bullock Scott, 2017).

The prime motive for quadrature amplitude modulation method (QAM) scheme is, its high spectral efficiency which can be attained by overlapping different carrier frequencies and therefore permitting the choice of proper constellation point for data transmission which allow the transmission of more data over the same frequency bands, Whereas QAM is used broadly in digital communication system (P & Didier Le, 2015; Pu & W, 2013).

5.3 Simulation Scenarios and Results:

The simulation and validation process are subdivided into sub-simulation cases or scenarios where different parameters are taken into account such as modulation order, amount of noise, number of pilot tones and so on. Thus, the simulation cases allow the analysis of different channel estimator performance and compare them to the proposed deep learning channel estimation model in the sense of bit errors bits rate (BER) to SN-ratio (SNR).

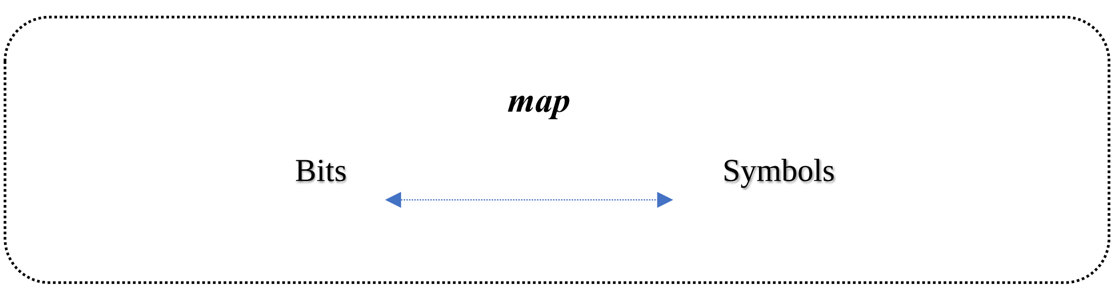
5.3.1 Testing and Validation Case-1:

According to the first scenario of testing and validation process in which we have use the following simulation parameters listed in the table below:

Table 5. 1: Case-1 Simulation Parameters.

Number of Pilots	64
Type of Modulation	4QAM
Constellation Points	4
Channel Estimation Method	MMSE, LS & Deep Learning Model
SNR Value	10 dB

The key emphasis of this simulation scenario is the type of modulation , modulation order and the noise imposed on the system in dB, hence we have used in this first scenario 4QAM digital modulation system where in this modulation type the user data signal is converted int digital data stream and the data stream is grouped as 2-bit groups also known as symbols, then these symbols are used to encode (modulate) the amplitude and phase of the carrier wave (Deergha, 2015; Rodger E & William H, 2015).



Therefore, the subcarriers used to carry the user digital input data and the constellation diagram which is used to group the digital input data into groups of symbols are shown graphically fig (5.1) and figure (5.2) for the 4QAM method, respectively.

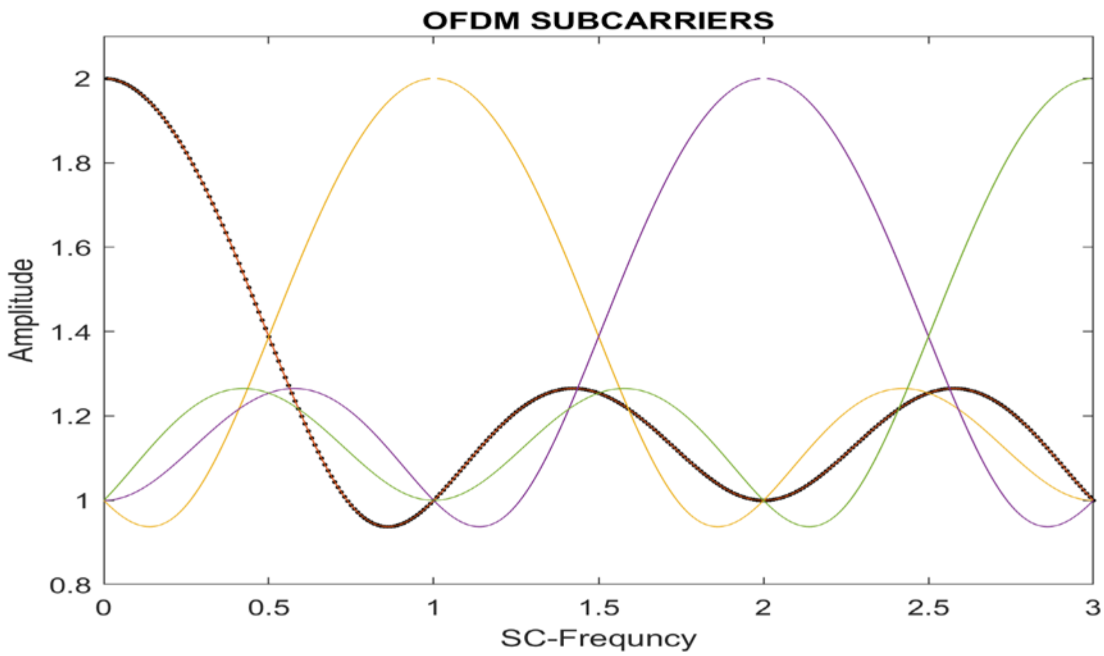


Figure 5. 1: 4QAM Syst - Subcarrier Spectrum.

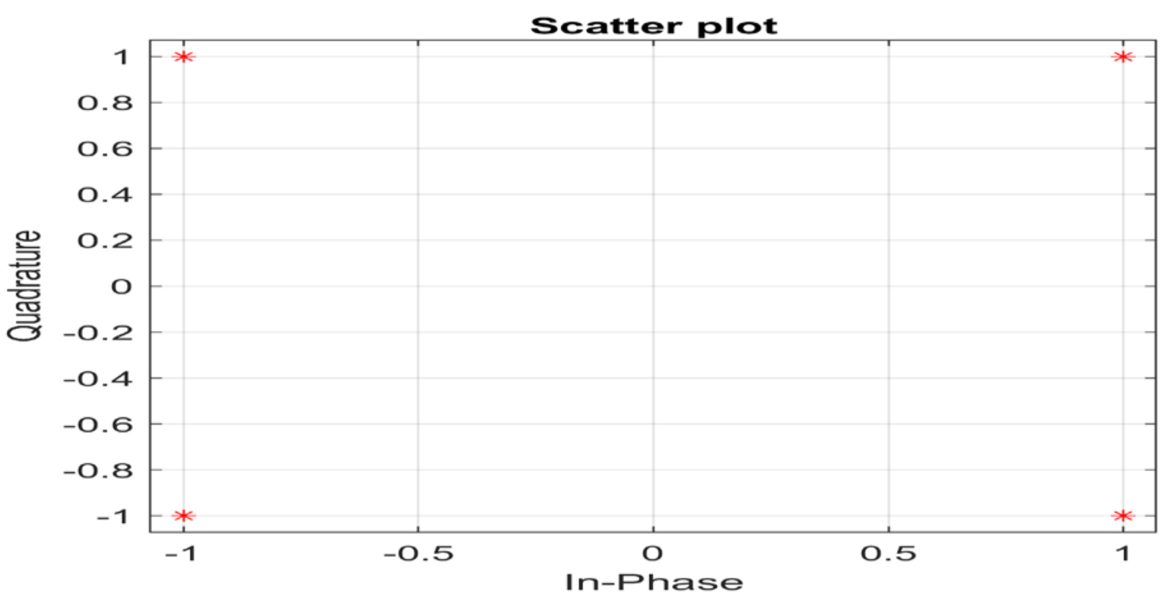


Figure 5. 2: 4QAM Syst - Constellation Diagram.

Now we turn our attention to the training process after generating the required 5G data and modulate the user data by using 4QAM modulation system, as we can see the training progress is monitored and plotted as follows:

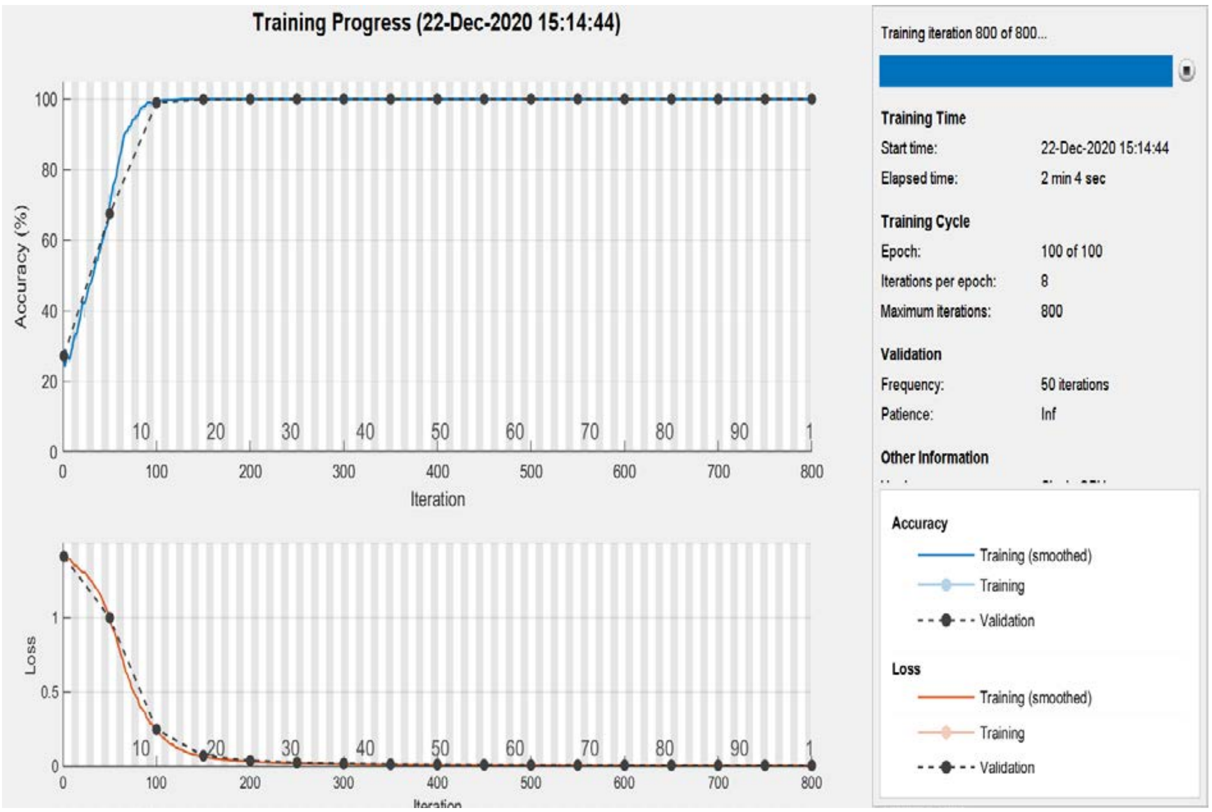


Figure 5. 3: Training Progress of 4QAM / 10 dB-SNR System.

The ultimate goal of the training process is to train the proposed deep learning model by using training data where the trained model can have ability to recovered user data signals at the receiver side through the implementation and utilization of the channel estimation concept.

As we can see there are three techniques used to perform the channel estimation and signal recovery at the receiver which-are:

- MMS-Error Method.
- Least-SE Method.
- LSTM Deep Learning method.

The proposed model by this thesis uses LSTM-“long short-term memory” D-learning technique to achieve channel estimation and recover the transmitted signal from the received signal accurately Compared to the conventional methods of canal approximations for reference, such as minimum mean square error and LSE-method. The output of testing process is shown as follows:

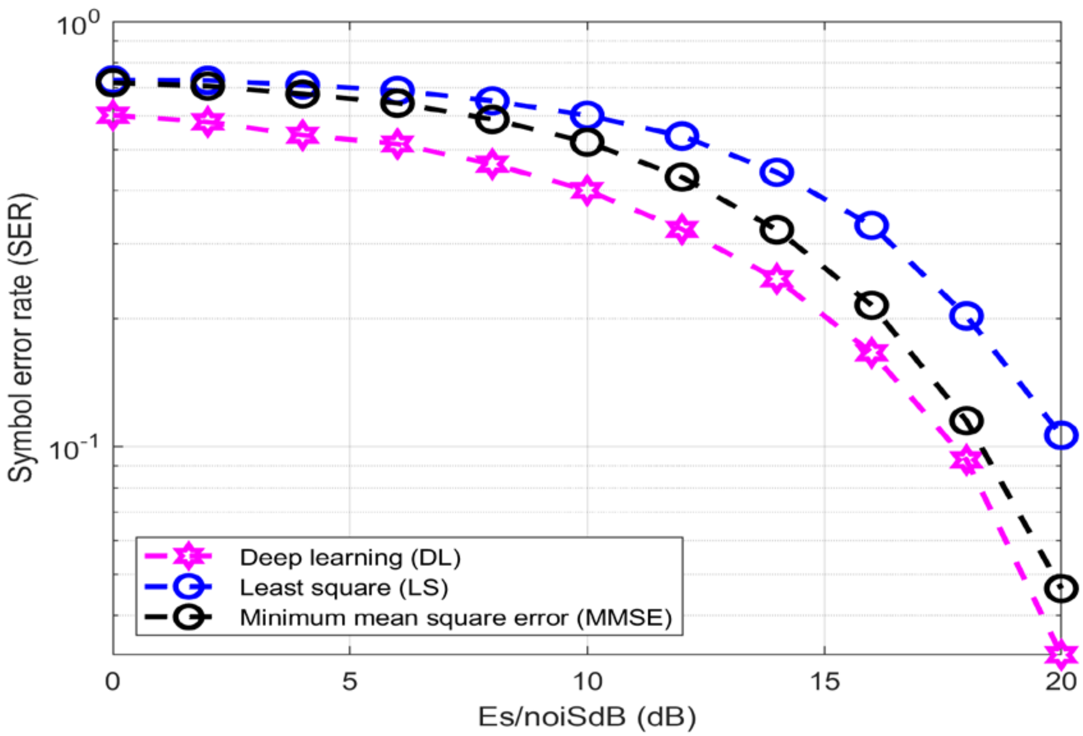


Figure 5. 4: Case-1 Testing Output Result of 4QAM / 10 dB-SNR System.

5.3.2 Testing and Validation Case-1 Observations:

Consider the above figure (5.3) which shows the training process we observe that the actual training accuracy is shown by the blue curve while the validation accuracy is shown as the black dashed curve in which the validation accuracy is approximately 100% while the actual training loss is zero. Looking at figure (5.4) which shows the output result of the testing process we observe the following, the proposed LSTM deep learning model has a lower symbol error rate (SER), while SER deceases with the ratio of the SN increasing (SNR) on top of that in our implementation we have kept the SNR level as 10 dB at the transmitter which is as low as possible to obtain the desired result. Hence, we conclude that the efficiency of the suggested model is more accurate as in relation to the performance of the MMSE and LS techniques. Correspondingly form the above figure (5.4) we realize the performance of minimum mean square error technique is better than the performance of the least square method in term of SER to SNR value. But for the SNR range from 0 to 3 dB the MMSE and LS have mostly the same BER values while beyond 5 dB-SNR the MMSE outperform the LS technique in estimating the channels.

5.3.3 Testing and Validation Case-2:

Considering the second scenario of testing and validation process where we have used the following simulation parameters listed in the table below:

Table 5. 2: Case-2 Simulation Parameters.

Parameters	Specification
Number of Pilots	64
Type of Modulation	8QAM
Constellation Points	8
Channel Estimation Method	MMSE, LS & Deep Learning Model
SNR Value	20 dB

This simulation scenario puts an emphasis on the modulation order and the noise imposed on the transmitted signal which is 20 dB, hence we have used in this second scenario an 8QAM digital modulation scheme. Therefore, the subcarriers and the constellation diagram are seen in figure (5.5) and figure (5.6) respectively for the 8QAM technique.

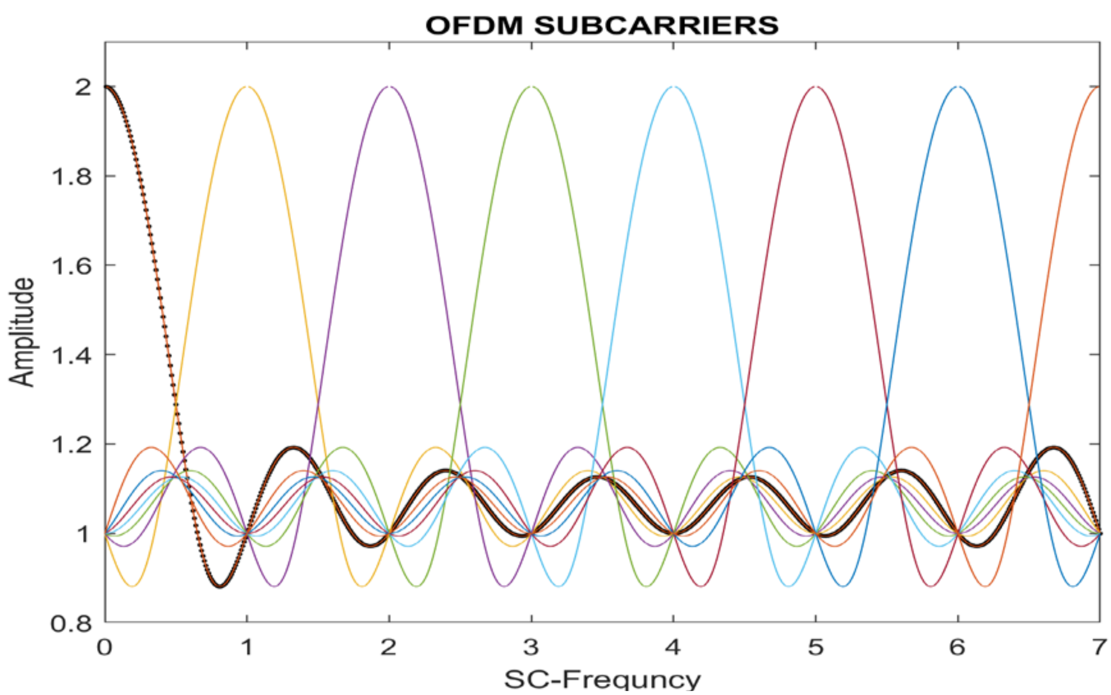


Figure 5. 5: 8QAM Syst - Subcarrier Spectrum.

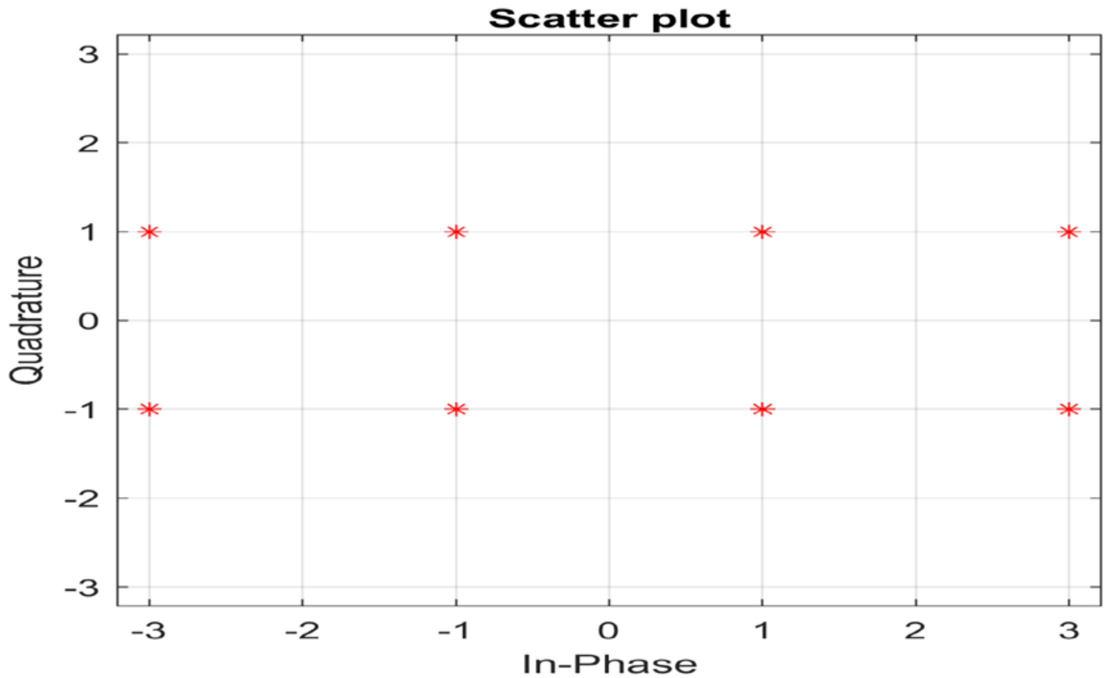


Figure 5. 6: 8QAM Syst - Constellation Diagram.

Now we consider the training process after generating the required 5G data and modulate the user data by using an 8QAM modulation system, as we can see the training progress is monitored and plotted as follows:

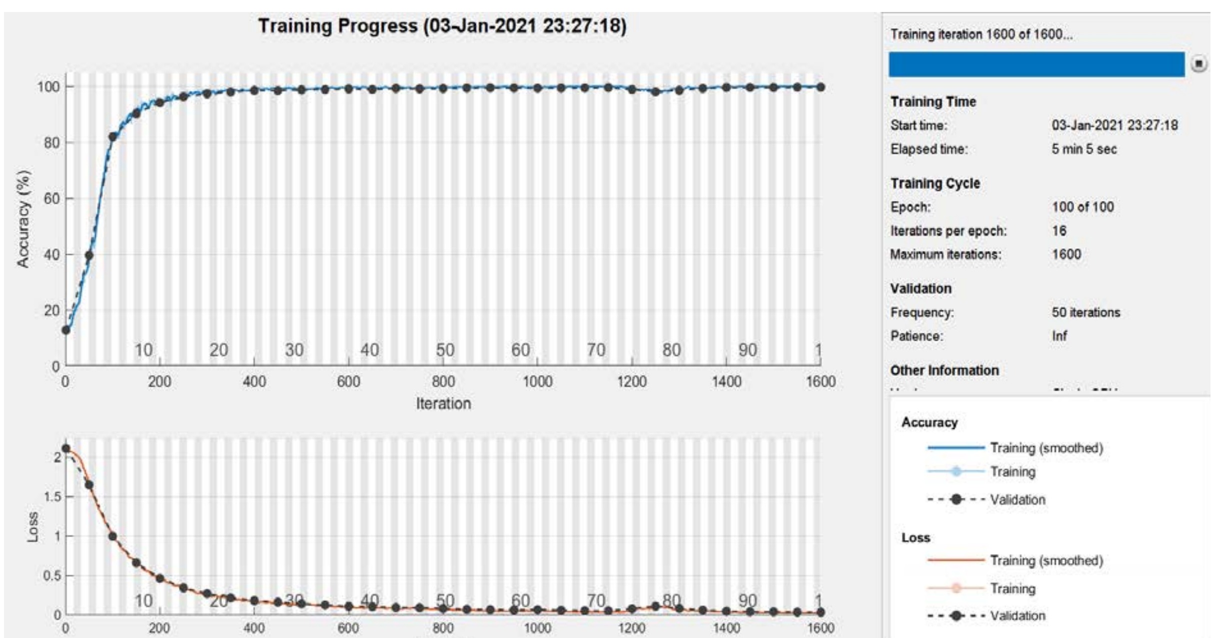


Figure 5. 7: Training Progress of an 8QAM / 20 dB-SNR System.

The output of testing process when using an 8QAM modulation scheme with a SNR-“signal to noise ratio” at the transmitter side is shown as following figure (5.8):

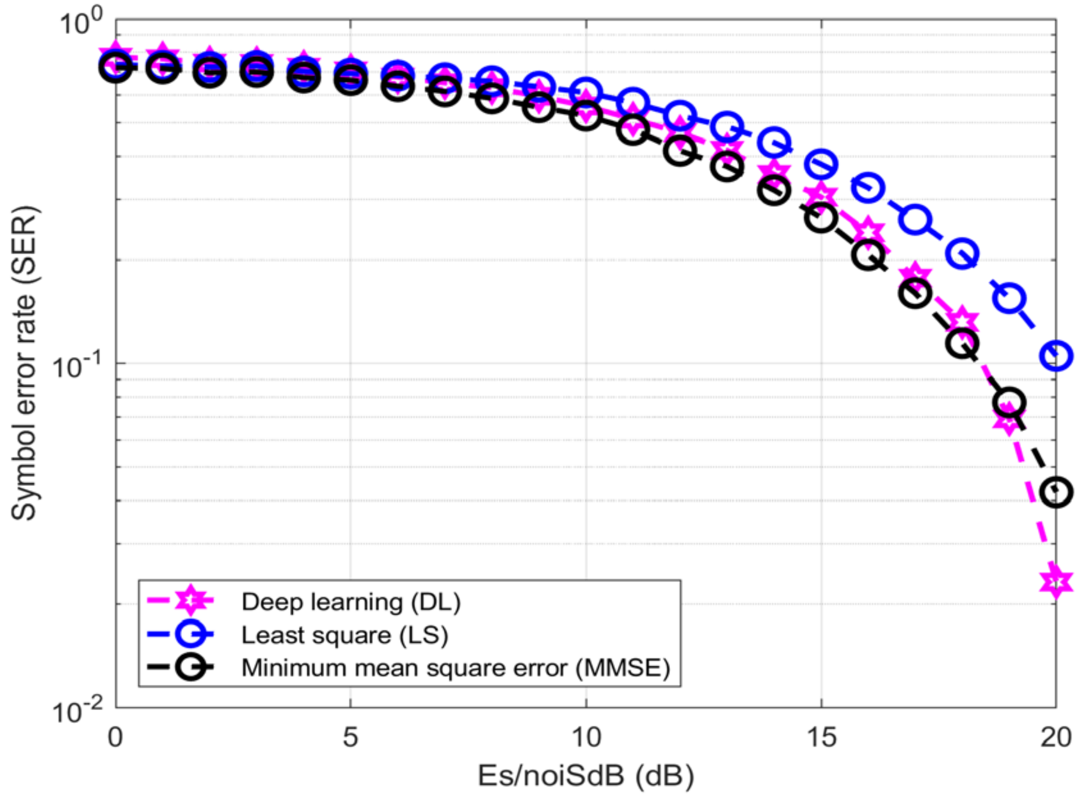


Figure 5. 8: Case-2 Testing Output Result of an 8QAM / 20 dB-SNR System.

5.3.4 Testing and Validation Case-2 Observations:

Contemplate the above figure (5.7) which shows the training process for the second scenario we can see that the training accuracy and the validation accuracy curves are very close to each other in term of values. And hence we have achieved a validation accuracy which is approximately 99% with a loss less than 1%. Observing figure (5.8) which shows the output result of the testing process when using 8QAM we observe that at the beginning of the testing process the proposed LSTM deep learning model, MMSE and LS methods have an identical performance regarding the symbol error rate (SER) in comparison to the ratio of signal/noise (SNR). Thus, when the SNR value start to exceed 7 dB the proposed deep learning model begin to outperform the MMS-error and LSE techniques as we can observe by looking at the output result curves. Hence, we conclude the following the effectiveness of the model in question is more accurate as in relation to the performance of the MMSE and LS techniques when a certain ratio of a signal/noise is imposed on the input data symbols.

5.3.5 Testing and Validation Case-3:

In view of the third scenario of testing and validation process where we have used the following simulation parameters listed in the table below:

Table 5. 3: Case-3 Simulation Parameters.

Parameters	Specification
Number of Pilots	64
Type of Modulation	16QAM
Constellation Points	16
Channel Estimation Method	MMSE, LS & Deep Learning Model
SNR Value	20 dB

In this simulation case the modulation order used is 4 bits/symbol and the noise enforced on the transmitted signal which is 20 dB, hence we have used in this third simulation case a 16QAM digital modulation system. The subcarriers and the constellation diagram are plotted graphically in figure (5.9) and figure (5.10) for this system.

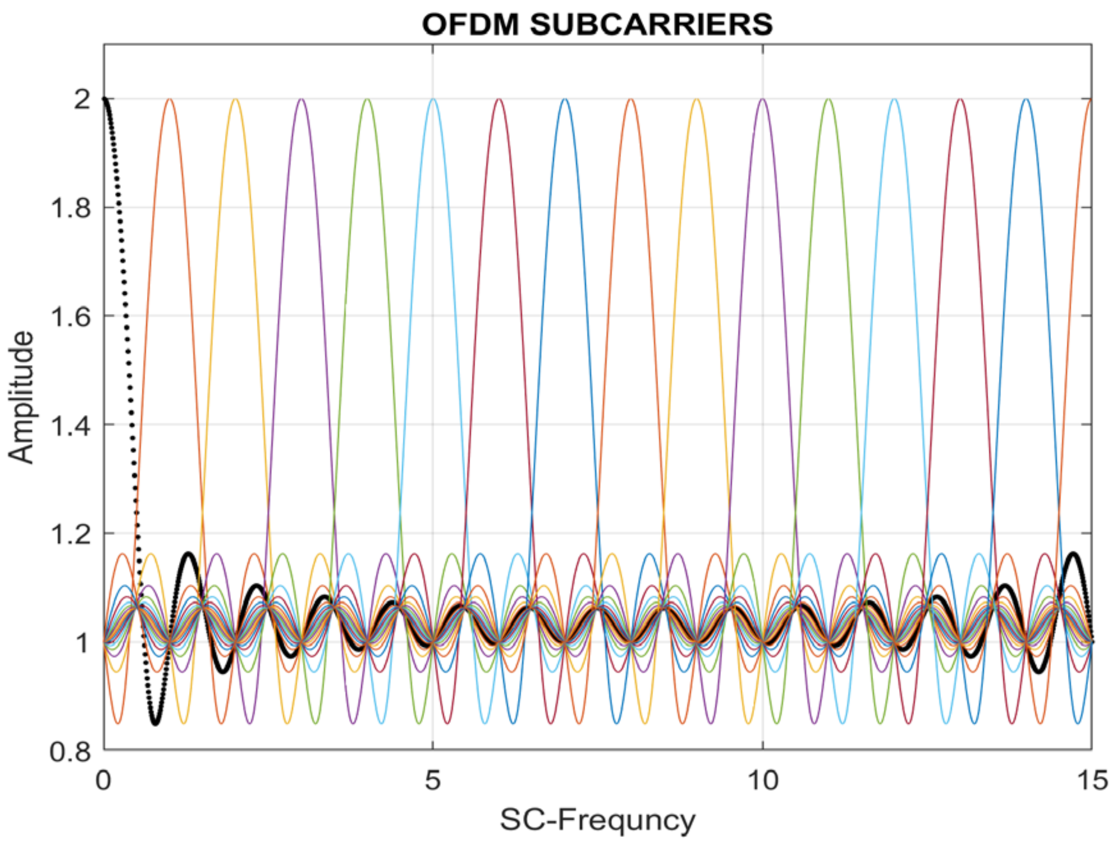


Figure 5. 9: 16QAM Syst - Subcarrier Spectrum.

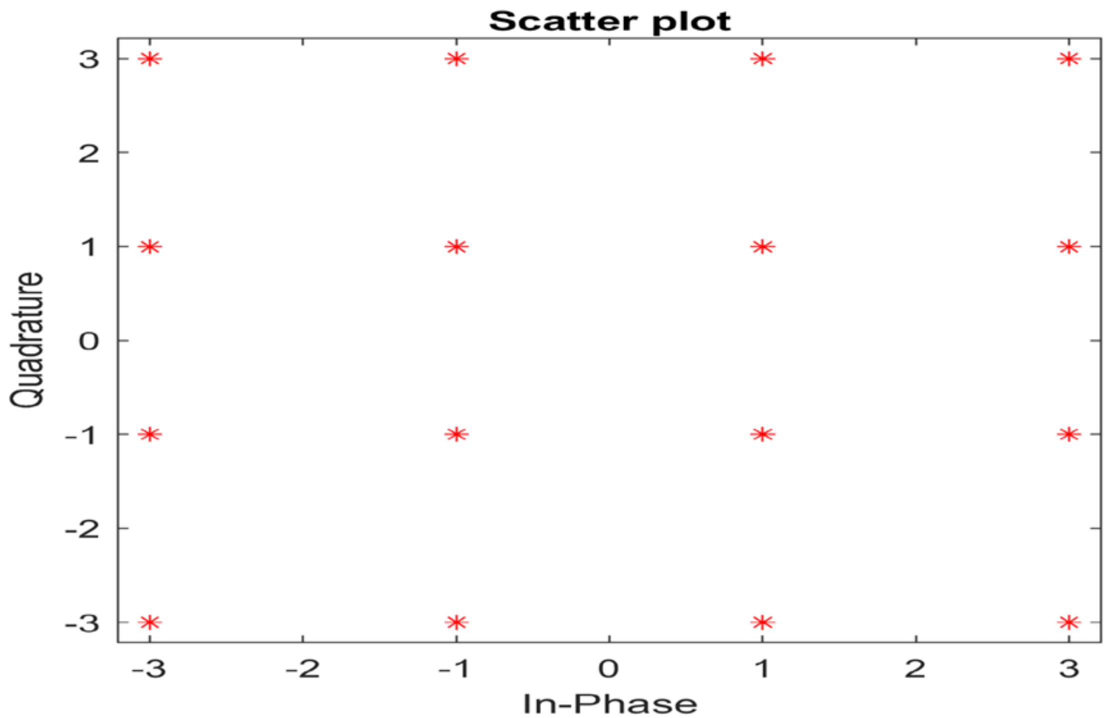


Figure 5. 10: 16QAM Syst - Constellation Diagram.

When take into account the training process by using a 4 bits/symbol modulation order to generate the required 5G data and modulate it, such training progress is monitored and graphed as follows:

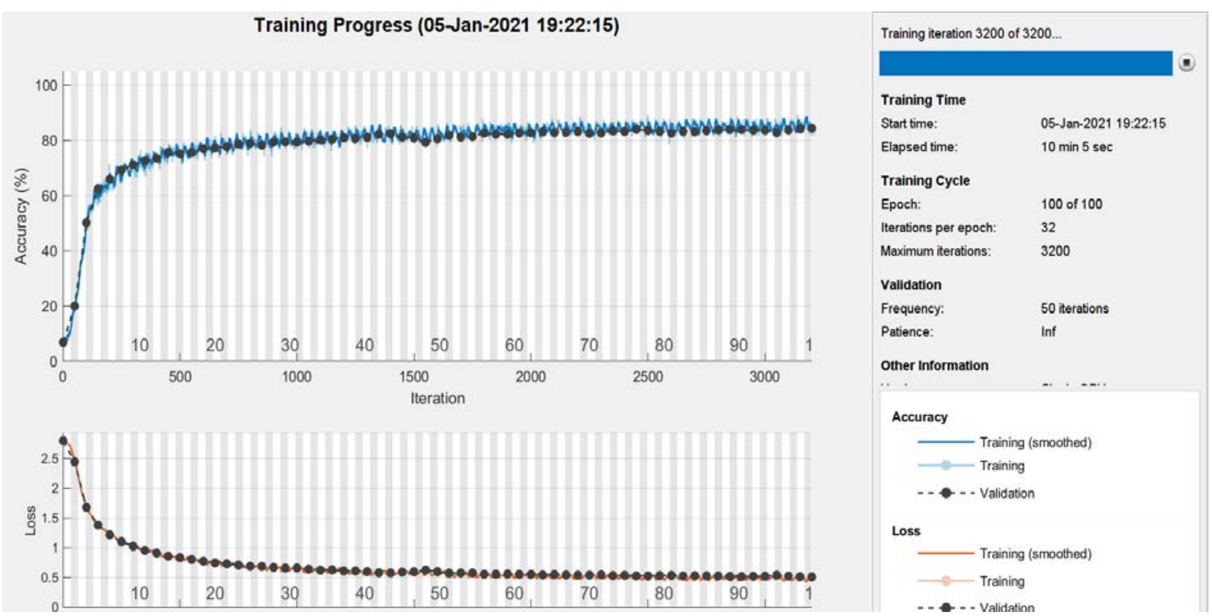


Figure 5. 11: Training Progress of 16QAM / 20 dB-SNR System.

Then after performing the training phase we perform testing phase and yield an output of testing process while using a 16QAM modulation scheme with a 20 dB ratio of SN (SNR) at the transmitter section while such an outcome is shown in the below figure (5.12):

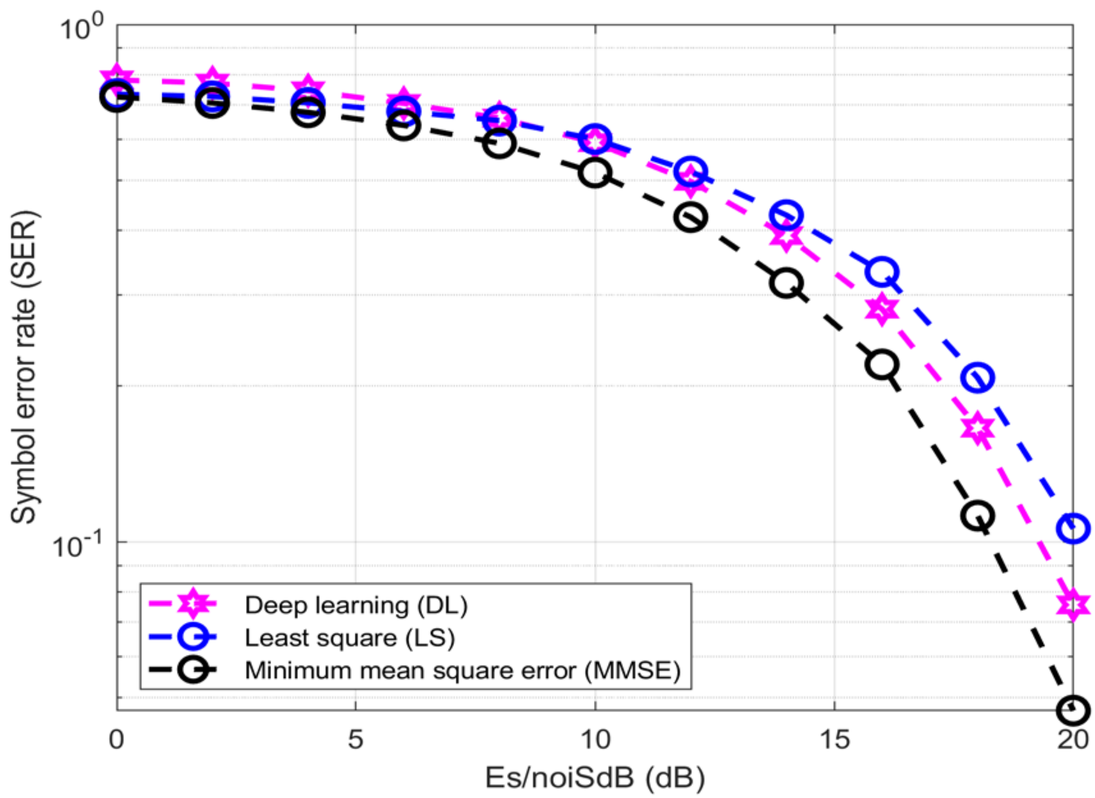


Figure 5. 12: Case-3 Testing Output Result of 16QAM / 20 dB-SNR System.

5.3.6 Testing and Validation Case-3 Observations:

Considering the above figure (5.11) which shows the training process for the third scenario we can see that the training accuracy and the validation accuracy curves of the proposed deep learning model are identical. While we have attained a validation accuracy which is approximately 83.29% with a loss less than 17%.

From figure (5.12) which shows the output result of the testing process when using 16QAM and 20 dB SNR value at the transmitter we observe that at the proposed LSTM deep learning model worse SER compared to MMSE method and have a better SER level compared to LS technique. Therefore, we can conclude the following at low SNR value used by the transmitter the proposed model does not perform well and it is ability to estimate the channel is hindered by the transmitter SNR level hence such model can be useful in some few specific situations.

5.3.7 Testing and Validation Case-4:

According to the fourth testing and validation scenario we have used the following simulation parameters listed in the table below:

Table 5. 4: Case-4 Simulation Parameters.

Parameters	**Specification**
Number of Pilots	64
Type of Modulation	16QAM
Constellation Points	16
Channel Estimation Method	MMSE, LS & Deep Learning Model
SNR Value	30 dB

The training progress when we use a 16QAM / 30 dB SNR level by the transmitter is plotted shown below:

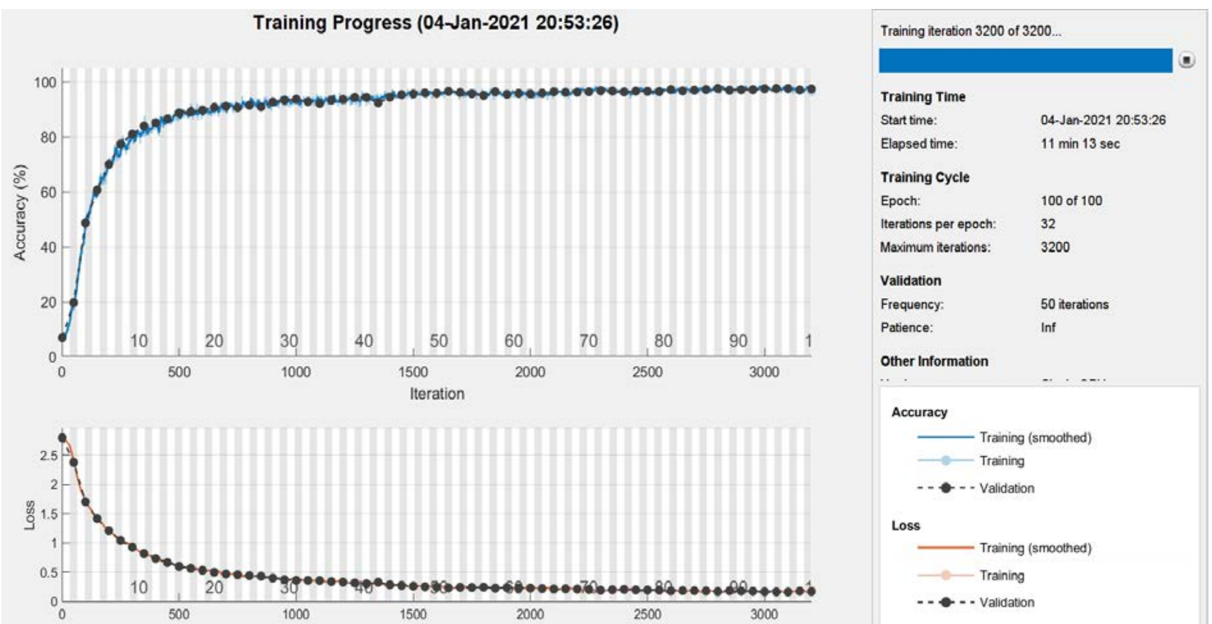


Figure 5. 13: Training Progress of 16QAM / 30 dB-SNR System.

Then after performing the training phase we perform testing phase and yield an output of testing process while using a 16QAM modulation scheme with a 30 dB ratio of signal by noise (SNR) at the transmitter section where such result is shown in the below figure (5.14):

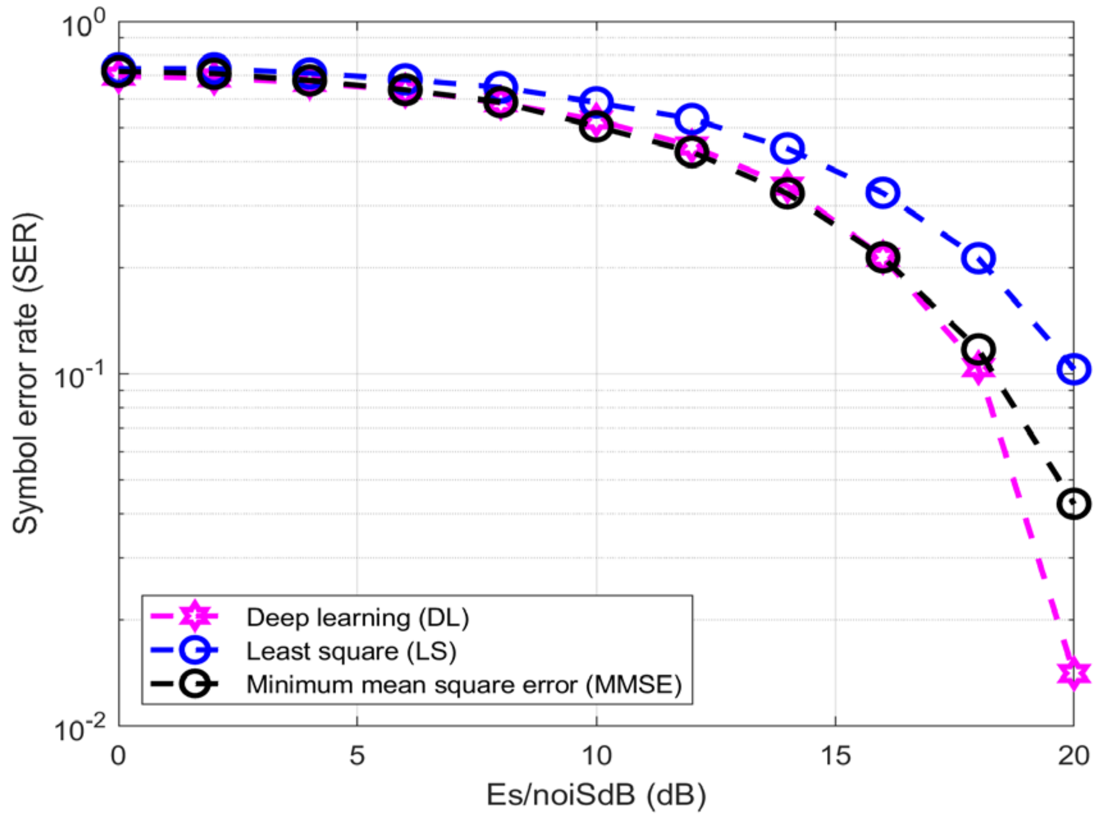


Figure 5. 14: Case-4 Testing Output Result of 16QAM / 30 dB-SNR System.

5.3.8 Testing and Validation Case-4 Observations:

Considering the above figure (5.13) which shows the training process for the third scenario we can see that the training accuracy and the validation accuracy curves of the proposed deep learning model are identical. While we have attained a validation accuracy which is approximately 95.80% with a loss less than 5%.

From figure (5.14) which shows the output result of the testing process when using 16QAM we observe that at the beginning of the testing process the proposed LSTM deep learning model, MMSE method have an undistinguishable performance regarding the symbol error rate (SER) in comparison to the "signal to noise ratio (SNR)". Then when the SNR value start to exceed 15 dB SNR the proposed deep learning model begin to beat the performance of the other two channel estimation techniques. Despite the low input SNR value, the performance of the proposed model still considered as decent.

5.3.9 Testing and Validation Case-5:

According to the fifth simulation situation scenario of testing and validation process where we have used the following simulation parameters listed in the table below:

Table 5. 5: Case-5 Simulation Parameters.

Parameters	**Specification**
Number of Pilots	64
Type of Modulation	16QAM
Constellation Points	16
Channel Estimation Method	MMSE, LS & Deep Learning Model
SNR Value	40 dB

The training process is monitored as shown in the following figure (5.15) where we mainly increase the SNR value at the transmitter side which gave an improve in the validation accuracy from 95% to 97%:

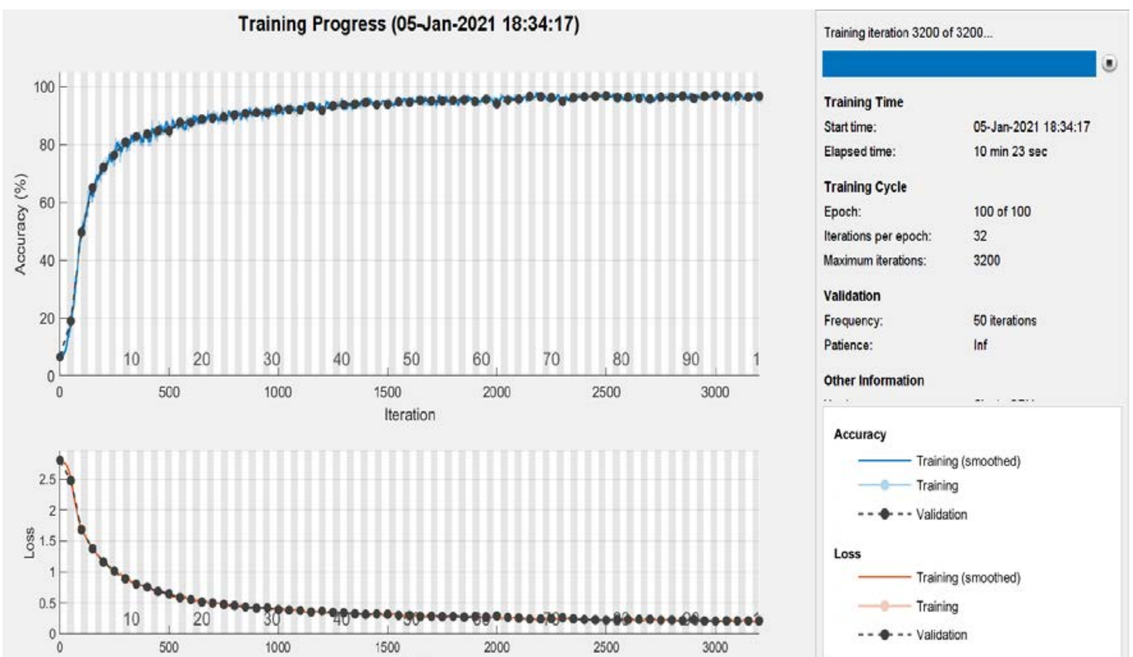


Figure 5. 15: Training Progress of 16QAM / 40 dB-SNR System.

While using a 16QAM modulation scheme with a 40 dB SN-ratio (SNR) at the transmitter section and such an outcome is shown in the below figure (5.16):

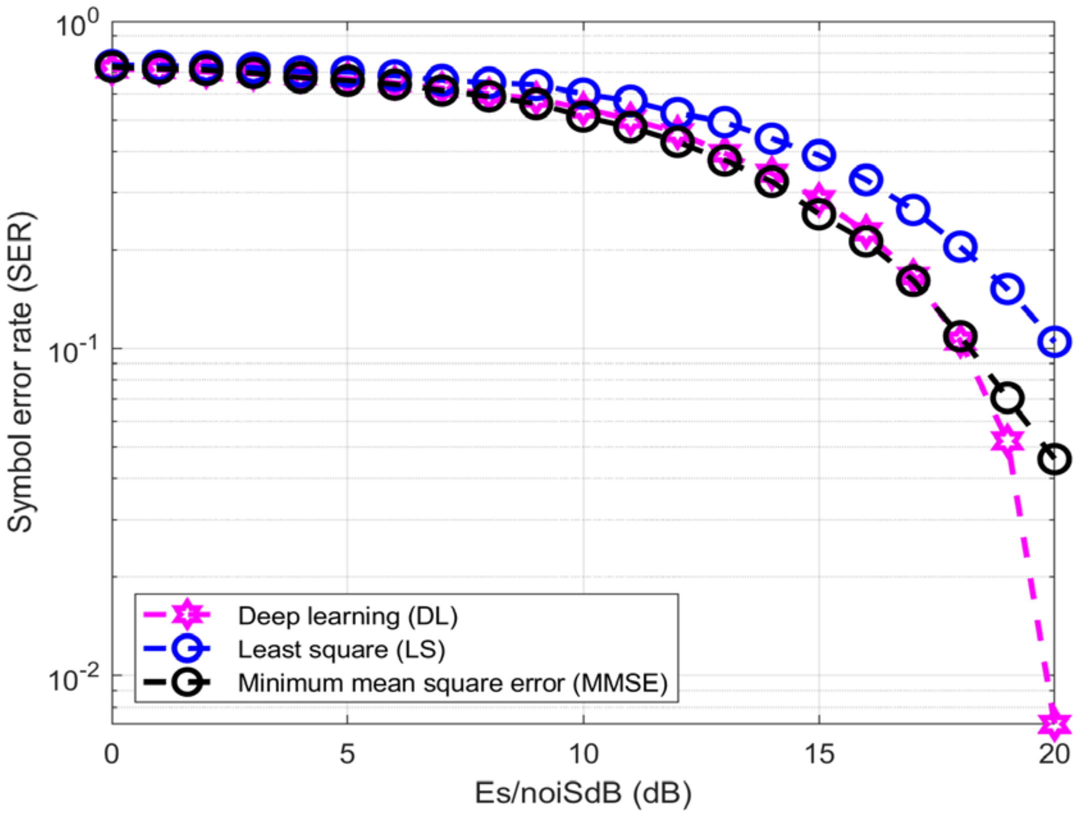


Figure 5. 16: Case-5 Testing Output Result of 16QAM / 40 dB-SNR System.

5.3.10 Testing and Validation Case-5 Observations:

In Accordance to the above figure (5.15), the training process for the fourth scenario we can see that the training accuracy and the validation accuracy curves of the proposed deep learning model are more smoothed compared to case-5 when using a 40 dB SNR level. While we have attained a validation accuracy which is approximately 97.56% with a loss less than 3%.

From figure (5.16) which shows the output result of the testing process when using 16QAM / 40dB we observe that the testing process of the proposed LSTM deep learning model, shows the proposed model have a better SER value compared to the above testing and validation cases discussed earlier.

5.4 Testing and Validation Cases Comparison:

The following table shows a brief comparing of training and validation accuracies and we can draw some few key points:

Table 5. 6: Comparison of Training and Validation Accuracies.

Mod-Order	SNR (dB)	T- Time (m)	T-Accuracy (%)	V-Accuracy (%)	T-Error (%)	V-Error (%)
4QAM	**10**	**02.40**	**100**	**100**	**0**	**0**
8QAM	**20**	**05.50**	**99**	**99**	**~1**	**~1**
16QAM	**20**	**11.80**	**83**	**83**	**~17**	**~17**
16QAM	**30**	**12.70**	**95**	**95**	**~5**	**~5**
16QAM	**40**	**11.13**	**97**	**97**	**~3**	**~3**

Considering the above table (5.6), we can express the following key points:

- For 4QAM and 8QAM system the proposed model has a good channel estimation validation accuracy which is approximately 100% accurate.
- For the 16QAM / 20 dB the proposed model has low validation accuracy and in turn it has low channel estimation capability and that due to the high modulation MCS rate with a low SNR.
- For the 16QAM / 30 dB and 16QAM / 40 dB the proposed model produces a satisfactory validation accuracy which is above 95%, and the due to minimum fulfilment of the required SNR value.

6. Future Scope and Conclusions

6.1 Conclusions:

The central goal of this work was to build a deep learning channel estimation and signal recovery model for 5G-cellular communication systems and deploying this model over several design scenarios and different input circumstances. Thus, in this report, we have studied and analyzed baseline channel estimation techniques, then we have designed a deep leaning model to estimate 5G channel and recover the user data as accurately as possible. The scenarios considered in this thesis were mainly depend on varying the input SNR level plus varying the modulation and coding scheme rate while comparing the performance and accuracy of the proposed model with two main channel estimation baseline method which are the minimum mean square error technique and the least square technique.

The quadrature amplitude modulation (QAM) system was chosen as the reference modulation system for all presented scenarios due to many reasons. The first reason it is QAM is a higher-order modulation type thus It is capable of holding more bits of data per symbol, as a result, the system rate of data can be improved by selecting a higher order format of QAM. The second reason is that the efficient QAM usage of bandwidth which is a result of QAM represent a greater number of bits per carrier frequency.

In chapter-1 offer a general and ephemeral explanation of cellular communications system, history of wireless communication systems, then it explains in details OFDM system, 5G-communication system, important features of 5G systems, thesis motivation, thesis objectives, and thesis problem statement.

In chapter-2, we have made a theoretical description on the concept of radio channel, literature review of current state of art regarding the thesis topic and scope, concept of channel estimation and channel estimation baseline techniques such training symbols-based methods and non-training symbol methods, and mathematical modeling of MMSE and LS techniques.

According to chapter-3 of this work, we present the definition of M-learning, M-learning types, M-learning applications, concepts of D-learning, deep learning working aspects, deep learning approaches used for channel estimation, advantages of deep learning, the proposed model by this thesis, and the reasons behind choosing deep leering approaches for this work .

Chapter-4, comprise of description and implementation of the most appropriate and important assumptions about the proposed model, and simulating the desired model in MATLAB environment. The model has the purpose of providing channel estimation and signal recovery of the user data transmitted by the transmitter side. The process of deep learning model generation starts with specifying the model parameters, generating 5G data through the use of appropriate standard such as 5G-3GPP standards, noise and channel impairment specification, specifying 16QAM as the main modulation system.

The important point behind the chapter is to generate the correct and valid 5G data to be used for training and validation process of the model in hand. While focusing on the LSTM as the backbone of the deep learning model.

In chapter-5, The testing and validation process of the proposed model is materialized and introduced, therefore here we generated testing data and used it as the transmitted user data while we passed the received data through the designed deep learning model in chapter-4 plus using MMSE and LS technique to perform channel estimation and recover the transmitted user data from the received version and differentiated the precision of the deep learning model in opposition to the MMSE and LS approaches.

In addition to that in this chapter we have divided the concept of testing the model in scenarios where we varied the input signal to noise ratio and the modulation coding scheme and analyzed the output result of the model with respect to the Sym-error rate, (“SER”) in relation to SN-ratio (“SNR”).

In chapter-6, we have presented conclusion and comment on the working performance of the designed model in comparison to other channel estimation method, then we mention a brief point about the future utilization and usage of the proposed model.

6.2 Future Scope:

Due to rapid advances in technology the performance of the cellular communication systems is unquestionably will be heightened in near future with the application such advanced and modern practices and technologies. As we know from recent years the development of cellular communication systems it is never a steady or slow growth in fact it is surprisingly faster than what we can expect.

In future scope, the proposed channel estimation model by this report can be extended and upgrade through the use of the following recommendations:

- Using another modulation technique other than QAM such as GMSK.
- Using other channel models and studying the effect of the channel on the SER.
- Investigating the performance of OFDM system by using other methods than FFT.
- Reviewing the deep learning model approach and using other deep learning approaches.

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RESUME

PERSONAL INFORMATION

Name Surname: Hamouda .M .H .M Hussain

Place of Birth: Khartoum, Sudan

Email: hamouda.mohammed.96@gmail.com

EDUCATION

Masters of Science in Electrical and Electronics Eng.– *Istanbul Aydin University, Istanbul – Turkey*

Graduated - April 2021 (**With 3.81 CGPA Out of 4**).

Bachelors of Electronics and Communication Eng.– *Gujarat Technological University, India*

Graduated - June 2018 (**With 9.21 CGPA Out of 10**).

Diploma of Telecommunication Engineering – *Alneelian University, Sudan*

Graduated - January 2011 (**With Percentage: 93.08 %**).

High School Diploma – *Khartoum - Sudan*

Graduated - Jun 2006 (**With Percentage: 77.30 %**).

WORK EXPERIENCE

Haddad international Co. Led (HICO) - *Khartoum, Sudan* *May 2011 – Apr 2014*

Telecommunication Technical Engineer

Responsible of Telecommunication Equipment Operation and Maintenance.

- Installations, Commissioning and Maintenance of Ericsson RBS 6000 Family (3G – Family).

- Installations, Commissioning and Maintenance of Ericsson RBS (2206, 2216, 2101, 2106).
- Installations and Commissioning of Microwave Links (ML - TN2p, ML - TN 20p, ML - CN 500).
- Installations and Commissioning of Huawei Radio Sys. such as (OptiX RTN 950).

Alshrooq Automobile Repair Center - *Khartoum, Sudan* *Feb 2007 - Apr 2011*

Electronics Technician

Responsible of Automobile Electronics Equipment installation and Maintenance.

- Installing Car GPS system.
- Electrical Fault Diagnostics and Repair.
- Various Automobiles ECU Fault Diagnostics.
- Locating mechanical Faults and Rectification.

CERTIFICATIONS

Sudatel Telecom Academy - Diploma - *Khartoum, Sudan* *2011*

Telecommunication Professional Diploma, Sudan Telecommunication Academy, Sudan, 89%.

Neo Creative Vision Pvt. Ltd. – *Ahmedabad – India*
2017 Workshop on Industrial PLC Controllers and SCADA Software.

Cisco Certified Associate Network (CCNA) – *Istanbul – Turkey*
2021 Currently Preparations are Ongoing.

PUBLICATIONS

- A Wireless Weather Monitoring System Using Arduino DUE and GSM Technology
  2018 **IRJET - journal**, “https://www.irjet.net/archives/V5/i4/IRJET-V5I4165.pdf”

LANGUAGE COMPETENCIES

- Arabic: native language.
- English: fluent (speaking, reading, writing).
- Turkish: Basic (speaking, reading); intermediate (writing).
- Hindi: Basic (speaking); intermediate (Understanding), Zero (Reading, Writing).

PROFESSIONAL SKILLS

- Good knowledge of PYTHON and C++ in real world applications.
- Excellent Command over MATLAB, Multisim, PORTEUS and HFSS.

- Mastery of Microsoft Office programs (Word, Excel, PowerPoint).
- Excellent communication skills with a focus on team-building.
- Outstanding organizational, multitasking, Fast learner and problem-solving abilities.