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SUBJECT

**Using Deep Learning To Investigate Massive
MIMO Hybrid Beamforming Design**

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In the name of Allah, the Most Gracious and the Most Merciful, And prayers and peace be upon the holy Prophet Mohammed.

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DEDICATION

This thesis is dedicated to:

For the sake of God our Creator, Master, Teacher and Great Messenger Muhammad (may God be pleased with him) who taught us the purpose of life.

*To my father «**Khodja said**», may God have mercy on him.*

*Our mothers «**Merzougi Hayat**», «**Saouchi Khadra**» and fathers «**Guelmine Layachi**» And to my dear sister «**khodja Rouqia**» and her dear husband «**Elmawed Ahmad**» for their endless love, support and encouragement, to our beloved brothers and sisters « **Khodja Salsabil ,khodja Marwa, Khodja Mahmoud, Khodja Farouk** ».*

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Table of Abbreviation

4G: Fourth generation.

5G: Fifth generation.

AB: Analog beamforming.

ADC: Analog-to-digital converter.

BS: Base-station.

cm-Wave: Centimetre wave.

CSI: Channel state information.

D2D: Device to device.

DAC: Digital-analog converter.

DB: Digital beamforming.

DC: Digital combining.

FDD: Frequency division duplex.

IoT: Internet of things.

LTE: Long term evaluation.

OMP: Orthogonal matching pursuit.

MIMO: Massive multiple-input multiple-output.

mm-Wave: Millimeter Wave.

MU-MIMO: Multi-user multiple-input multiple-output.

OFDM: Orthogonal frequency-division multiplexing.

PS: Phase shifter.

RF: Radio frequency.

RX: Receiver.

SE: Spectral efficiency.

SNR: Signal-to-noise ratio.

SVD: Singular value decomposition.

TDD: Time division duplex.

TDMA: Time-division multiple access.

TX: Transmitter UE User equipment.

EE: Energy efficienc.

ZF: Zero forcing.

$\mathbf{F}^{\text{AB}}$: Analog precoder.

$\mathbf{F}^{\text{DB}}$: Digital precoder.

N_{RF} : Number of RF chains.

N_{S} : Number of data streams.

N_{cl} : Number of clusters.

N_{ray} : Number of multipath rays.

$\mathbf{W}^{\text{AB}}$: Analog combiner.

$\mathbf{W}^{\text{DB}}$: Digital combiner.

General introduction

GENERAL INTRODUCTION

In the near future, beyond 4G, some of the prime objectives or demands that need to be addressed are increased capacity, improved data rate, decreased latency, and better quality of service. To meet these demands, drastic improvements need to be made in cellular network architecture. This thesis studies the beamforming design based on deep learning in MIMO technology. Traditional MIMO systems employ digital beamforming where each antenna element is equipped with one radio frequency (RF) chain. When the number of the antennas are scaled up, the cost and power consumption of massive MIMO systems also increase significantly. Recently, hybrid analog-and-digital beamformers have attracted a lot of attention as a cost effective approach to benefit from the advantages of massive MIMO. In hybrid structure, a small number of RF chains are connected to a large number of antennas through a network of phase shifters. The optimal hybrid beamforming problem is a complex non convex optimization due to the non convex constraint imposed by phase shifters. The overall objective of this thesis is to provide simple and effective hybrid beamforming solutions for narrowband point-to-point and multiuser massive MIMO scenarios.

Motivation

The 5G physical layer will depart from 4G LTE in a number of ways, in order to improve spectral efficiency and data rates. One distinctive feature is a significant jump in the number of active antennas and antenna arrays, and the related issues of beamforming and millimeter wave RF signal processing. New modulation and coding schemes, power and low-noise amplifier designs, and channel models all need to be developed. Future wireless access will extend beyond people, supporting connectivity for any element that may benefit from being connected. One of the key motivators is to provide ubiquitous, high-speed, high-quality wireless broadband coverage to meet societal and industrial needs beyond 2020.

Statement of the problem

5G will solve issues that have plagued existing technologies for years, such as pixelated video calls, long buffer times for streamed movies, and delays between uploading and sharing content. and we need to find the optimal number of streams which maximizes the spectral efficiency of the beamforming system. Spectral efficiency, spectrum efficiency or bandwidth efficiency refers to the information rate that can be transmitted over a given bandwidth in a specific communication system. Spectrum in the mmWave band will provide localised coverage as they only operate over short distances.

Is providing higher bandwidth efficiency(spectrum efficiency) capacity than current 4G—supporting broadband , 5G will enable a higher density of mobile broadband users and support ultra reliable device-to-device and massive machine-type communications.

Report outline

Our work was divided into 4 chapters:

- **The First Chapter:**

In this part we talk about the different generation of mobile networks and the last one 5G, and its structure and use families, and we studied the difference between the 4th generation and the fifth generation.

- **The Second Chapter:**

In it, we talk about the characteristics of the fifth generation of mobile network and the technologies used in it, which are: Massive MIMO, Small Cell, MM wave, Hybrid beamforming, Full Duplex.

- **The Third Chapter:**

We talk about machine learning deep learning and its different architectures and we chose CNN architecture (the convolutional neural network) to study it in our work and use it in our project. Then we examined how the CNN architecture affects spectral efficiency and compared it with other deep learning algorithms.

CHAPTER I

5G Technology

1.1 Introduction

The main goal of previous generations of mobile networks was simple to provide fast and reliable mobile data services to network users. 5G has extended this reach to offer a wide range of wireless services, delivered to the end user across multiple access platforms and over multi-sofa networks. 5G is actually a dynamic, cohesive and flexible framework for multiple advanced technologies supporting a wide variety of applications. 5G uses a smarter architecture, with wireless access networks (RANs) that are no longer subject to the constraints of proximity to the base station or complex infrastructure. 5G paves the way for a disaggregated, flexible and virtual wireless access network (RAN) with new interfaces creating additional data access points. Today and in the recent future, to fulfill the presumptions and challenges of the near future, the wireless based networks of today will have to advance in various ways. Recent technology constituent like high-speed packet access (HSPA) and long-term evolution (LTE) will be launched as a segment of the advancement of current wireless based technologies. Never the less, auxiliary components may also constitute future new wireless based technologies, which may adjunct the evolved technologies. Specimen of these new technology components are different ways of accessing spectrum and considerably higher frequency ranges, the instigation of massive antenna configurations, direct device to-device communication, and ultra-dense deployments [1].

1.2 The Different Generations ('G's)

wireless communications have become an important part of present day society. Since satellite communication, television and radio transmission has advanced to pervasive mobile telephone, wireless communications has transformed the style in which society runs. The evolution of wireless begins here [2] and is shown in Fig. 1. It shows the evolving generations of wireless technologies in terms of data rate, mobility, coverage and spectral efficiency. As the wireless technologies are growing, the data rate, mobility, coverage and spectral efficiency increases. It also shows that the 1G and 2G technologies use circuit switching while 2.5G and 3G uses both circuit and packet switching and the next generations from 3.5G to now i.e. 5G are using packet switching. Along with these factors, it also differentiate between licensed spectrum and unlicensed spectrum. All the evolving generations use the licensed spectrum while the WiFi, Bluetooth and WiMAX are using the unlicensed Spectrum. An overview about the evolving wireless technologies is below:

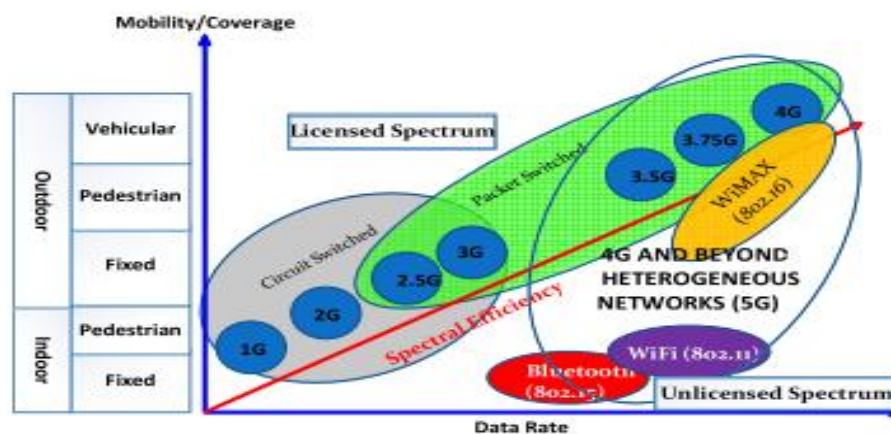


Figure 1.1: Evolution of wireless technologies.

A. 1G

The 1st generation was announced in initial 1980's. It has a data rate up to 2.4kbps. Major subscribers were Advanced Mobile Phone System (AMPS), Nordic Mobile Telephone (NMT), and Total Access Communication System (TACS). It has a lot of disadvantages like below par capacity, reckless handoff, inferior voice associations, and with no security, since voice calls were stored and played in radio towers due to which vulnerability of these calls from unwanted eavesdropping by third party increases [7].

B. 2G

The 2nd generation was introduced in late 1990's. Digital technology is used in 2nd generation mobile telephones. Global Systems for Mobile communications (GSM) was the first 2nd generation system, chiefly used for voice communication and having a data rate up to 64kbps. 2G mobile handset battery lasts longer because of the radio signals having low power. It also provides services like Short Message Service (SMS) and e-mail. Vital eminent technologies were GSM, Code Division Multiple Access (CDMA), and IS-95 [3],[7].

C. 2.5G

It generally subscribes a 2nd generation cellular system merged with General Packet Radio Services (GPRS) and other amenities doesn't commonly endow in 2G or 1G networks. A 2.5G system generally uses 2G system frameworks, but it applies packet switching along with circuit switching. It can assist data rate up to 144kbps. The main 2.5G technologies were GPRS, Enhanced Data Rate for GSM Evolution (EDGE), and Code Division Multiple Access (CDMA) 2000 [3],[7].

D. 3G

The 3rd generation was established in late 2000. It imparts transmission rate up to 2Mbps. Third generation (3G) systems merge high speed mobile access to services based on Internet Protocol (IP). Aside from transmission rate, unconventional improvement was made for maintaining QoS. Additional amenities like global roaming and improved voice quality made 3G as a remarkable generation. The major disadvantage for 3G handsets is that, they require more power than most 2G models. Along with this 3G network plans are more expensive than 2G [3],[7]. Since 3G involves the introduction and utilization of Wideband Code Division Multiple Access (WCDMA), Universal Mobile Telecommunications Systems (UMTS) and Code Division Multiple Access (CDMA) 2000 technologies, the evolving technologies like High Speed Uplink/Downlink Packet Access (HSUPA/HSDPA) and Evolution-Data Optimized (EVDO) has made an intermediate wireless generation between 3G and 4G named as 3.5G with improved data rate of 5-30 Mbps [3].

E. 3.75G

Long-Term Evolution technology (LTE) and Fixed Worldwide Interoperability for Microwave Access (WiMAX) is the future of mobile data services. LTE and Fixed WiMAX has the potential to supplement the capacity of the network and provides a substantial number of users the facility to access a broad range of high speed services like on demand video, peer to peer file sharing and composite Web services. Survey of 5G Network: Architecture and Emerging Technologies Along with this, a supplementary spectrum is accessible which accredit operators manage their network very compliantly and offers better coverage with improved performance for less cost [4],[7].

F. 4G

4G is generally referred as the descendant of the 3G and 2G standards. 3rd Generation Partnership Project (3GPP) is presently standardizing Long Term Evolution (LTE) Advanced as forthcoming 4G standard along with Mobile Worldwide Interoperability for Microwave Access (WiMAX). A 4G system improves the prevailing communication networks by imparting a complete and reliable solution based on IP. Amenities like voice, data and multimedia will be imparted to subscribers on every time and everywhere basis and at quite higher data rates as related to earlier generations. Applications that are being made to use a 4G network are Multimedia Messaging Service (MMS), Digital Video Broadcasting (DVB), and video chat, High Definition TV content and mobile TV [2] ,[4],[5].

G. 5G

With an exponential increase in the demand of the users, 4G will now be easily replaced with 5G with an advanced access technology named Beam Division Multiple Access (BDMA) and Non- and quasi-orthogonal or Filter Bank multi carrier (FBMC) multiple access. The concept behind BDMA technique is explained by considering the case of the base station communicating with the mobile stations. In this communication, an orthogonal beam is allocated to each mobile station and BDMA technique will divide that antenna beam according to locations of the mobile stations for giving multiple accesses to the mobile stations,[7], which correspondingly increase the capacity of the system. An idea to shift towards 5G is based on current drifts, it is commonly assumed that 5G cellular networks must address six challenges that are not effectively addressed by 4G i.e. higher capacity, higher data rate, lower End to End latency, massive device connectivity, reduced cost and consistent Quality of Experience provisioning Figure 1.2 .

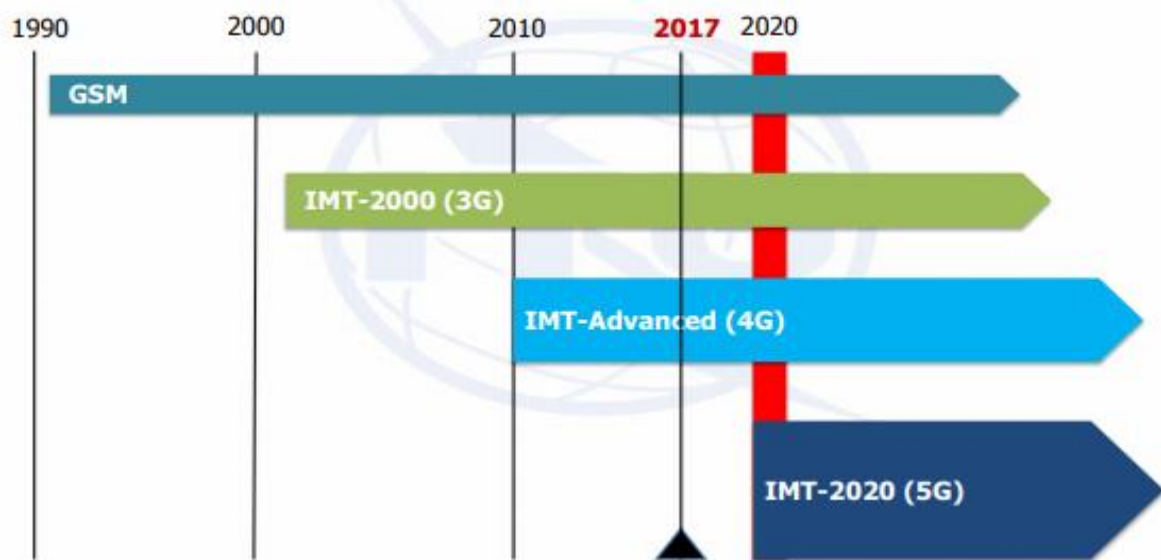


Figure 1.2: IMT Standards Evolution towards 5G

1.3 5G use families

Three main categories of uses (defined by ITU, under the term IMT-2020) Figure 1.3:

1.3.1 mMTC – Massive Machine Type Communications

Communications between a large number of objects with varying quality of service needs. The objective of this category is to respond to the exponential increase in the density of connected objects.

1.3.2 eMBB - Enhanced Mobile Broadband

Ultra-high speed connection outdoors and indoors with uniform quality of service, even at the edge of the cell.

1.3.3 uRLLC-Ultra-reliable and Low Latency Communications

Ultra-reliable communications for critical needs with very low latency, for increased responsiveness.

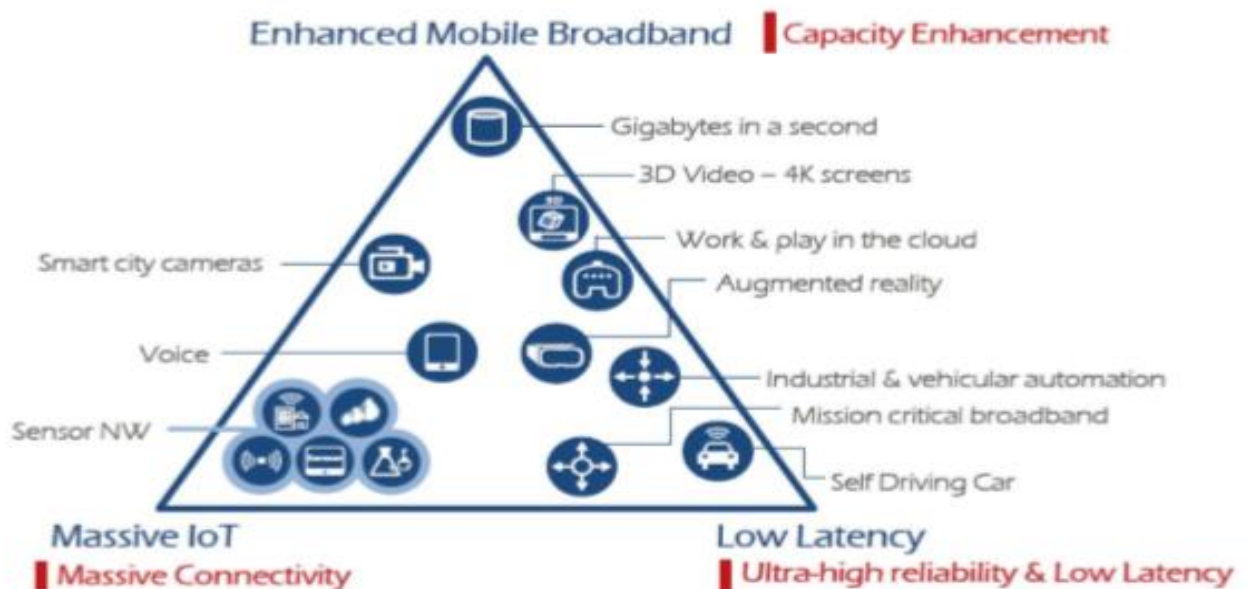


Figure 1.3:5G usage scenarios of IMT for 2020.

The first group (mMTC) mainly encompasses all uses related to the Internet of Things. These services require extensive coverage, low energy consumption and relatively low speeds. The announced contribution of 5G compared to current technologies lies in its ability to connect objects distributed very densely over the territory.

Ultra high speed (eMBB) concerns all applications and services that require an ever faster connection, for example to allow viewing of ultra high definition (8K) videos or wireless "streamer" of virtual reality applications. or increased.

Ultra-reliable ultra-low latency communications (uRLLC) encompass all applications requiring extremely high responsiveness as well as a very strong guarantee of message transmission. These needs are mainly found in transport (reaction time in the event of risk of an accident, for example), in medicine (telesurgery) and, in general, for the digitization of industry.

1.4 KPIs - Key performance indicators

In order to implement these three types of use, eight performance indicators have been established by the ITU to specify, quantify and measure the characteristics of IMT-2020 (5G) systems in the table 1.1 below:

Performance /Generation	4G	5G
1.Maximum throughput (Gbit / s)	1	20
2.Speed perceived by the user (Mbit / s)	10	100
3.Spectral efficiency (bit / Hz)	1x	3x
4. Speed (km / h)	350	500
5. Latence (ms)	10	1
6. Number of objects connected in an area (quantity of objects / km ²)	105	106
7. Network energy efficiency.	1x	100x
8. Throughput over an area (Mbit / s / m ²).	0.1	10

Table 1.1: Comparisons between 4G and 5G performance

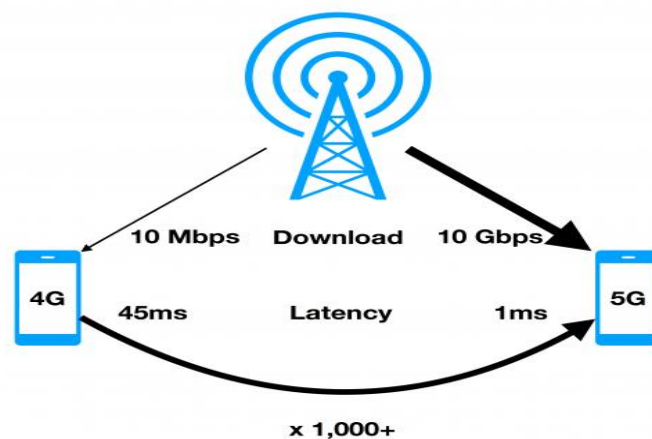


Figure 1.4:Comparison of 4G / 5G

1.5 5G NETWORK ARCHITECTURE

1.5.1 The Core Network

Is the mobile exchange and data network that manages all of the mobile voice, data and internet connections. For 5G, the 'core network' is being redesigned to better integrate with the internet and cloud based services and also includes distributed servers across the network improving response times (reducing latency). Many of the advanced features of 5G including network function virtualization and network slicing for different applications and services, will be managed in the core. The following illustration shows examples of local cloud servers providing faster content to users (movie streaming) and low latency applications for vehicle collision avoidance systems.

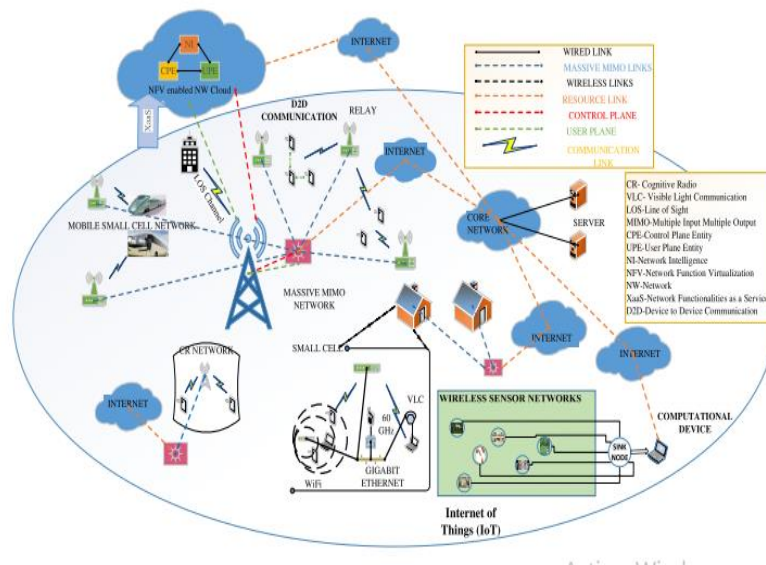


Figure1.5: A general 5G cellular network architecture.

Better scalability for handling the increasing number of the connected devices. For the vision of all-communicating world relative to today's network, the overall technical aim is to provide a system idea that supports [16] Figure 1.6:

- 1000 times increased data volume per area.
- 10 to 100 times increased number of connected devices.
- 10 to 100 times increased typical user data rate.
- 10 times extended battery life for low power Massive Machine Communication (MMC) devices.
- 5 times reduced End-to-End (E2E) latency.

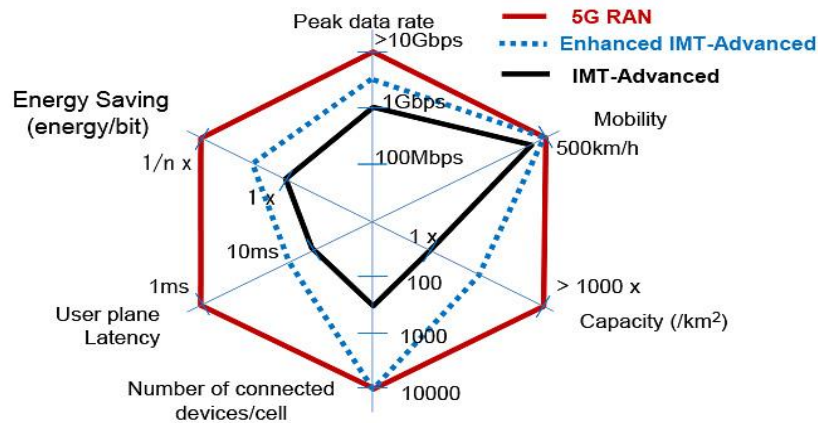


Figure 1.6: Requirements for 5G

We will research the below technology components [16]:

1.5.2 Radio-links

Includes the development of new transmission waveforms and new approaches of multiple access control and radio resource management.

1.5.3 Multi-node and multi-antenna transmissions

Includes designing of multi-antenna transmission/reception technologies based on massive antenna configurations and developing advanced inter-node coordination schemes and multi-hop technologies.

1.5.4 Network dimension

Includes considering the demand, traffic and mobility management, and novel approaches for efficient interference management in complex heterogeneous deployments.

1.5.5 Spectrum usage

Includes considering extended spectrum band of operation, as well as operation in new spectrum regimes to provide a complete system concept for new spectrum regimes that carefully addresses the needs of each usage scenario.

1.5.6 Device-to-Device(D2D) communications

Refers to direct communication between devices allowing local exchange of user plane traffic without going through a network infrastructure.

1.5.7 Massive Machine Communications (MMC)

Will form the basis of the Internet of Things with a wide range of application fields including the automotive industry, public safety, emergency services and medical field.

1.5.8 Moving Networks (MN)

Will enhance and extend linking together potentially large populations of jointly moving communication devices.

1.5.9 Ultra-dense Networks (UDN)

Will be the main driver whose goals are to increase capacity, increase energy efficiency of radio links, and enable better exploitation of under-utilized spectrum.

1.5.10 Ultra-reliable Networks (URN)

Will enable high degrees of availability.

1.6 Conclusion

Through our study in this chapter of the technology of the fifth generation of mobile network, it can be said that 5G will revolutionize communication technologies and change the usual lifestyle by supporting the Internet Of Things (IOT).

5G will provide extremely high bandwidth as well as more reliable connections to smart phones and other devices, allowing billions of devices to rely on a stable internet connection and process a huge amount of data with minimal delay.

It enhances artificial intelligence as well as cloud computing, and many sectors depend on new technology, and thus the fourth revolution.

CHAPTER II

5G enabling techniques

2.1 Introduction

The fifth generation (5G) of the cellular communication systems are required to provide very high data rates to support the user demands for various range of applications. The capacity of a single-user communication system depends on the system bandwidth and signal-to-noise ratio (SNR). Transmitting a high power signal over a large bandwidth can result in a very high data rate. However, this is not possible due to high power consumption, inter-cell and intra-cell interference effects and government regulations. Hence, an efficient use of spectrum and assuring a reasonable SNR levels at the receiver is crucial in order to meet the promise of high data rates in 5G. Multiple-input-multiple-output (MIMO) systems have attracted a lot of attention over the last decade as they can improve the transmission reliability as well as the spectral efficiency. The system reliability, also known as diversity, is improved by transmitting the signal over multiple links. The chance of having multiple links at a deep fading point decreases as the number of the antennas increases. Hence, the probability of receiving the correct signal at the receiver increases. The spectral efficiency can be improved by spatial multiplexing techniques and transmitting multiple symbols over the same time and frequency slot by spatial filtering. This is achieved by precoding and combining techniques at the transmitter and receiver, respectively. The received SNR can be improved by focusing the transmitted signal towards a desired spatial direction which is called beamforming.

The total number of the transmitted symbols over a wireless MIMO channel is upper limited by the minimum number of the base station antennas and the total number of the antennas at the user side. The more antennas are available at the base station, the more users can be supported and higher data rates can be achieved. In addition, large antenna arrays can provide pencil-beams by applying beamforming techniques. Consequently, a big portion of the power can be focused towards the intended user which results in higher receive SNR as well as lower interference among the rest of the users. the aforementioned advantages of equipping the base station with a large number of antennas, known as massive MIMO systems, has motivated many researchers in academia and industry to consider this technology as one of the major candidates for 5G. An overview of such systems and their advantages, challenges and application is presented in the next section.

2.2 Millimeter waves wireless communications

It is a frequency band called mmwave, which is one of the main parts of 5G technology. Its work cannot be completed unless the challenges facing mmwave are overcome. It is called thus because it is located in the frequency range between 30 - 300 GHz and the wavelength of the waves for this frequency is 1-10 mm, so that we know the relationship between Frequency and wavelength:

$$F = C/\lambda \quad (2.1)$$

Equation2.1: Frequency band.

F:frequency band

C: the speed of light 3×10^8 m/sec

λ : wave length

These calculations are important for knowing the length, height, or dimensions of the antenna used (antenna or transmitter) for this type of frequency.

2.2.1 Where is mmwave located

We know that the frequencies start from 1Hz-100 GHz we mean 1Hz one cycle per second and 1 GHz we mean one billion cycles per second. The frequencies used in wireless networks today are between 1Hz - 6GHz, including 2.6MHz and 900MHz used in wireless communications for mobile phones, then 100MHz; 2.4 GHz is currently present in WLAN wireless home networks beyond 555MHz; 5.2GHz is also used in local wireless networks. All of these provide us with a lower bandwidth of 1GHz. After 6GHz we see what is called Cmwave ranges between 6GHz - 30GHz, which is widely used, 28GHz is the frequency of the signal carrying other signals, and 1.3GHz is the ground of the band or the speed of transmission and reception that can be provided to users in this band, then comes the millimeter signals that provide us with 20GHz that range between 30GHz-300GHz. It includes the 39GHz and 60GHz band that provides the 7GHz bandwidth and the 10GHz E-Band are 70 and 90 but the most used in our world today is 60GHz ranging between 57-64GHz which is Bandwidth 2.7GHz because it is unlicensed meaning that anyone has the right to use it for industrial, scientific and medical applications and does not need License from responsible institutions for the countries concerned. One of the main pillars of the fifth generation of 5G communication generations is the Mmwave, and more precisely it is 60GHz Figure 2.1.



Figure 2.1: Millimeter Waves Wireless Communications

2.2.2 Millimetre waves advantages

- 1- The radio spectrum is still rather undeveloped.
- 2- More bandwidth is available.
- 3- Hence higher data rates is achieved.
- 4- Security and privacy is better at mm-wave.

Because mmwave is a wave transmission, most of the antennas used today for accuracy broadcast in all directions the same energy and the same power of the signal is transmitted and consumed in all directions, while mmwave is at a high frequency that leads to it not spread to a far distance in order to make it spread to a distance ranging between 10 meters and 100 or 200 meters, we need to make it Directionnal. This is called Beamforming. We note

here that the signal is a lobe or several lobes, any bundle of a narrow signal ranging from 1° from 360° to 20° or 30° , meaning that the beam is narrow compared to the 360° that was broadcast. It has stinks in the past or even at the present time. These important apps for Mmwave make it safer and more private. If there is a person communicating with the tower near it, the signal will be directional in one direction, meaning that the person next to it cannot eavesdrop on this signal, unlike what is present in the wireless communications used today. And because it is more secure and more directive, it is used in the Mmwave Backhaul, which is the links between the towers currently, most of the towers are wireless communication by fiber optic or others. network is buried underground and extended between these towers, while in the future the backhaul of the towers will be connected with some using Mmwave, and this will save us a very large cost that is reduced instead of digging and connecting the wires with some, the direct wireless communications and the directed communications may be less energy consuming than what is currently present. Up to 20 or 90 times, and several lobes can be broadcast at the same time, the towers are considered to be Base stations for these networks. It is possible to connect to the Line off site. Mmwave relay are small towers whose function is only to pass the signal to facilitate users far from the tower and to deliver the signal through directed beams. Directional beam, as well as we will have interfering base stations in every case of wireless communication, which is an interference between waves, for example, used if it aims to reach a tower that may collide. With him the signal coming from another tower, which is one of the problems that must be addressed.

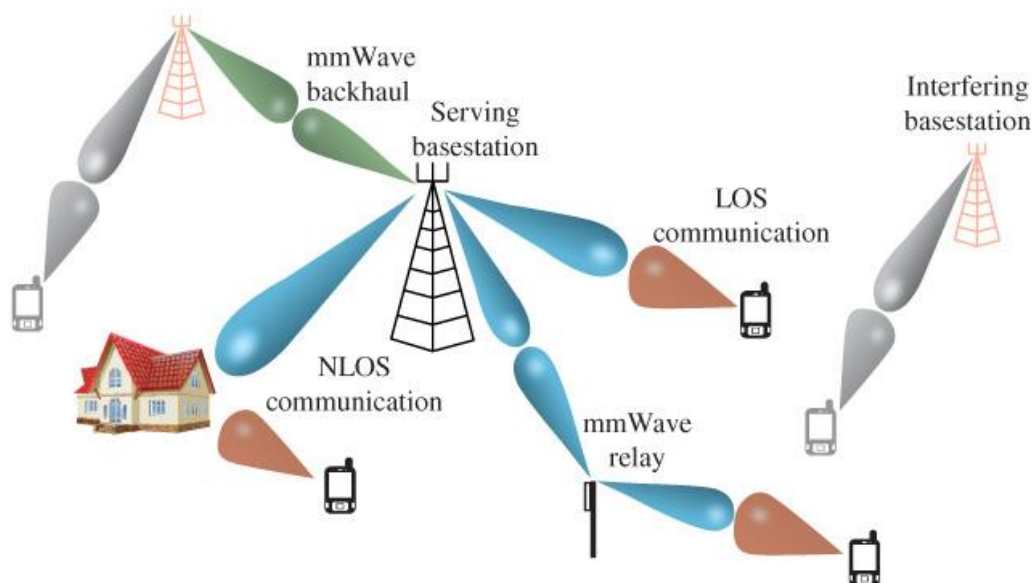


Figure 2.2 : Analysis of millimeter wave systems for 5G

2.2.3 Millimetre waves limitations

- 1- Higher costs in manufacturing of greater precision hardware due to components with smaller size.
- 2- At extremely high frequencies, there is significant attenuation. Hence millimeter waves can hardly be used for long distance applications.
- 3- The penetration power of mm-wave through objects such concrete walls is known less.
- 4- There are interferences with oxygen and rain at higher frequencies therefore further research is going on to reduce this.



Figure 2.3: Platforme to work on Mm-wave

RPU: Baseband processing Unit.

RX: Reception.

TX: Transmition.

Phased array: A group of stains arranged in a matrix within a single board.

Clock Board: Used in synchronization between receiver and transmitter.

2.3 Small Cells in 5G

2.3.1 What is a small cell

The beginning of small cell, when we hear this term, we envision a wireless network covering a very small area less than 6ft^3 of the type of plug in play, that is, simply linking to the power source and the internet source will be ready to work and any user who joins this network will be able to connect to the Internet directly from Its advantages are low power output, which means the antennas used in this network must be low power and thus reduce electrical energy consumption and low power consumption for antennas and users. Their devices also consume less energy than what is currently available. These networks are characterized by being limited capacity less than 128 users means capacity It has a few in the normal position and the area to be covered ranges from several meters to hundreds of meters, but not more than that. It must be small in size and coverage.

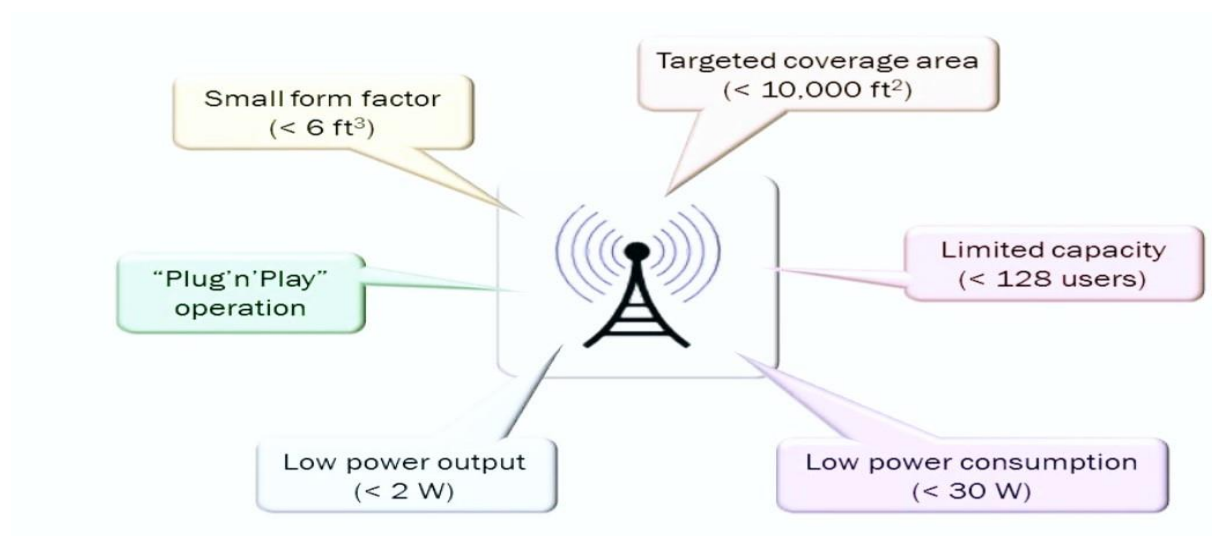


Figure2.4:Small Cells

2.3.2 Why we need Small cells

For users in today's world, 4G LTE, most of the users say that the internet that we have is fairly fast and covers all our needs, but this thing will not be continuous permanently because there are:

- More mobile users.
- More devices.
- More data required.
- More capacity and coverage.
- Increasing towers, allocate more spectrum, and use new technology are not enough.
- Solution is small cells.

Solution

- Adding more low power antennas in the field with lower footprint (coverage).
- Similar to (adding more towers) idea but with less power consumption, less users, less interference.
- Result: cheaper and more efficient network.
- Sometimes called: Self Organizing Networks (SON).

2.3.3 Types of small cells

The main advantage of these networks may be indoor or outdoor coverage, and they may only be outdoor, which is cheaper and less coverage for a smaller number of users (coverage radius) these networks are part of the other. As coverage radius and capacity increase, the network size also increases figure 2.5.

Indoor:	10-100mW	 Femto
Outdoor:	0.2-1W	
Coverage radius:	10s of meters	
Indoor:	100-250mW	 Pico
Outdoor:	1-5W	
Coverage radius:	10s of meters	
Outdoor:	5-10W	 Micro
Coverage radius:	100s of meters	
Outdoor:	>10W	 Macro
Coverage radius:	kilometer(s)	

Figure 2.5: Types small cells.

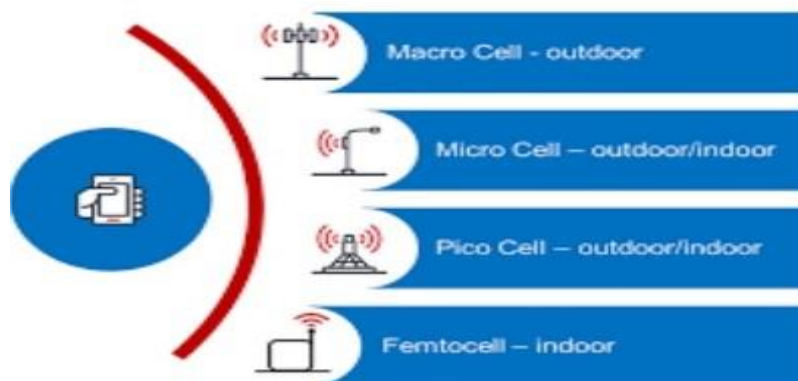


Figure 2.6: Different small cells in 5G.

2.4 What is Massive MiMo

Massive MIMO (Multiple Inputs-Multiple Outputs) this technology is characterized by the use of a high number of "intelligent" micro antennas, located on the same panel (from 8 to 128 currently, but the number will increase with use. Frequencies above 6 GHz). By MIMO we mean the presence of a group of antennas in the reception and a group in the transmitter that are currently present in the local or home networks, which began in the year 2009. We observe in one tower instead of we have one antennas, we have Hundreds of BS antennas which are the main station or the tower or acces point instead of what contains one antenna has become containing hundreds of antennas that can cover a large group of users instead of being a single antenna that sends and receives for each one of the users means one by one means having several antennas will make each one of these antennas assigned to one of the devices used and thus we will get a faster speed from the network figure 2.7.

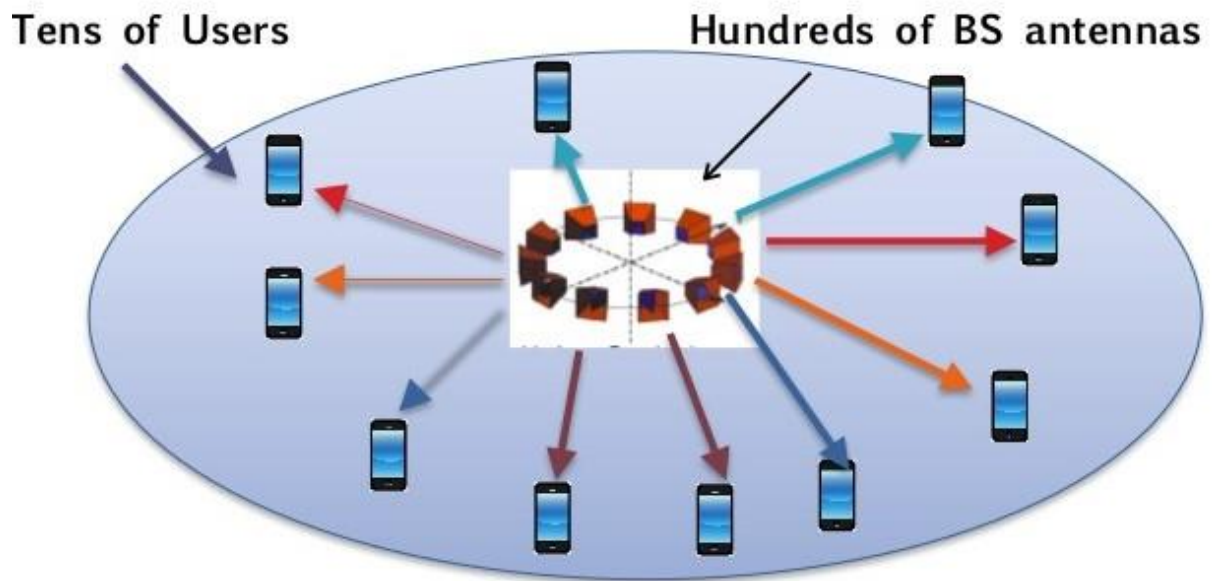


Figure 2.7: Essentially multiuser MIMO with lots of base station antennas.

- A very large antenna array at each base station.
- A large number of users are served simultaneously.
- An excess of base station(BS) antennas figure2.8.

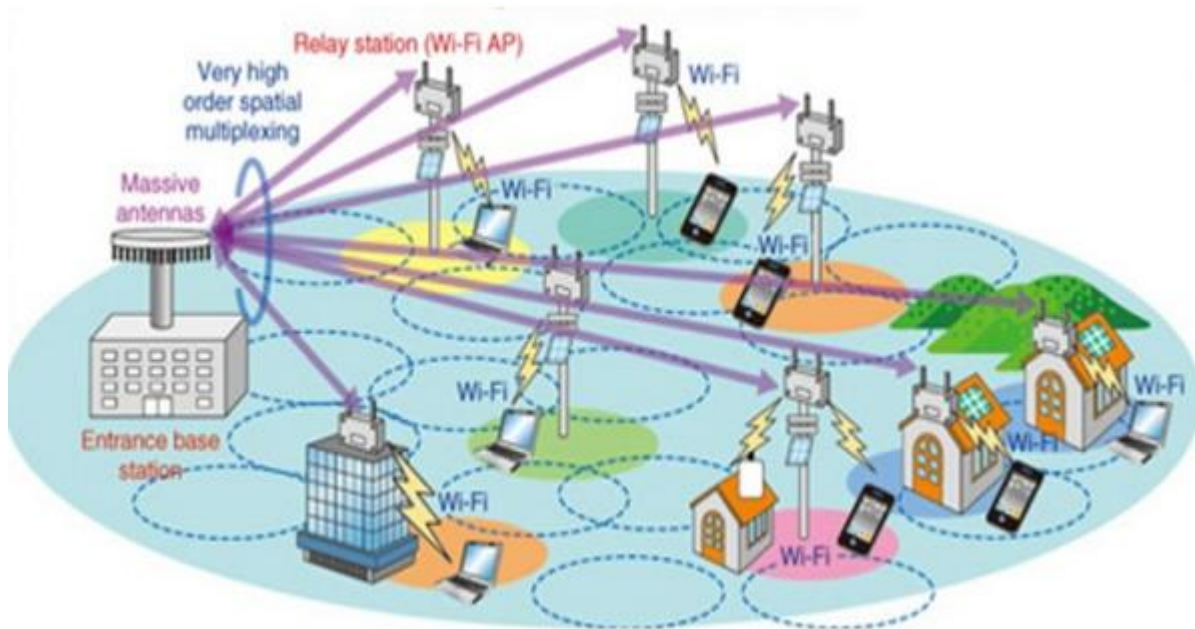


Figure 2.8: Massive MIMO

2.4.1 Overview of Massive MIMO

- As the name implies, Massive MIMO is an antenna array system using a massive amount of antenna.
- It is also called large scale MIMO.
- Then you may ask "How many antenna is required to be called 'Massive(Large Scale) MIMO'!".
- The answer may be different depending on how you design the receiver algorithm(equalizer design).
- We may need over 300 antenna. If you think is too big number, you may decrease the number by applying a little bit smarter receiver(equalizer) algorithm.
- In conventional LTE using a normal MIMO, the maximum number of antenna in MIMO as of now is 8×2 or 4×4 .

2.4.2 Multi user VS Single user

2.4.2.1 SU-MIMO

- The multiplexing gain may disappear when the signal power is low, relative to interference and noise, or in propagation.
- Environments with dominating line-of-sight or insufficient scatters.
- SU-MIMO systems also require complex and expensive multiple- antenna terminals.
- Practical size limitations on terminals also limit the number of antennas that can be used and thereby the achievable multiplexing gains[17].

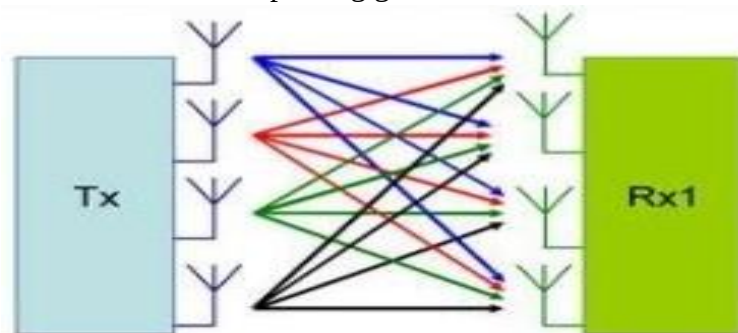


Figure 2.9: Single user MIMO 4 streams

2.4.2.2 MU-MIMO

- It is shown that all the effects of uncorrelated noise and fast fading disappear, as does the intra-cell interference.
- The only remaining impediment is the inter-cell interference due to pilot contamination[17].

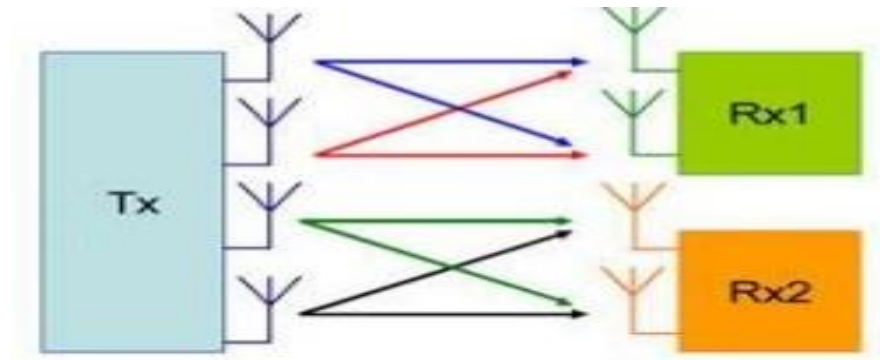


Figure 2.10: Multi user MIMO 2 user, 2 streams each.

2.4.3 Massive MIMO Features

- Massive (very large).
- Large transmitters / receivers(10 or 100 antennas).
- More signal paths.
- High data rate.
- Link reliability.
- Complexity increased.
- Equipment price increased.
- Number of RF amplifier.
- More energy consumption.
- Boost capacity.

2.4.4 5G VS 4G

4G There is one antenna present in BS and communicate with the devices one after the other, but the presence of a group of antennas at the same time will make each one to send and receive the device independent of the other device and thus the speed of transmission and reception of course this is in 5G. It transmits in all directions while antenna in 5G will be Directional using beamforming is the transmitter and receiver beam, which is a directing the power of the signal in one direction so that the power is very strong, but it is very weak in the other directions figure 2.11.

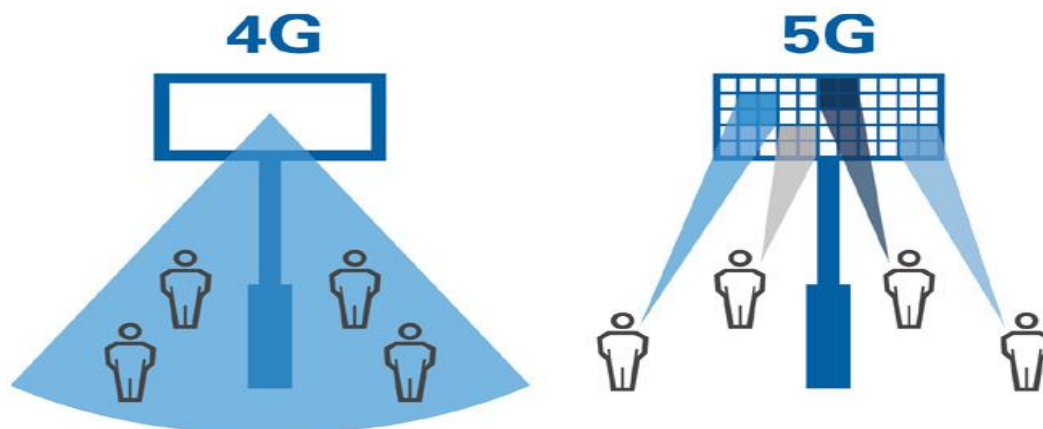


Figure 2.11: 4G VS 5G

2.5 What is Beam-forming

It is a technique used to focus the energy emitted from the antennas in a specific direction, and thus the energy or power will increase in this direction with a specific user and decrease in other directions, and thus interference will decrease in other places in the new generation. The energy will be concentrated in a specific direction. The beam instead of what is 360° in all directions will be the beam. It ranges between $3-30^\circ$ and thus the beam will be narrow and the energy directed in a certain direction and thus will allow an increase in the emission of energy in a certain direction because the fifth generation networks use the frequencies mm is 60 GHz and therefore the wavelength will be very small and the distance that will be covered will be less than the distance covered by the current networks that use 2,4; 5GHz, so concentrating energy in a specific direction in a narrow beam allows it to reach farther distance. This main function of beamforming is to make the energy emitted from antennas instead of being scattered in all directions be focused in a specific direction and thus will travel a longer distance and reach the user with a stronger signal figure 2.12.

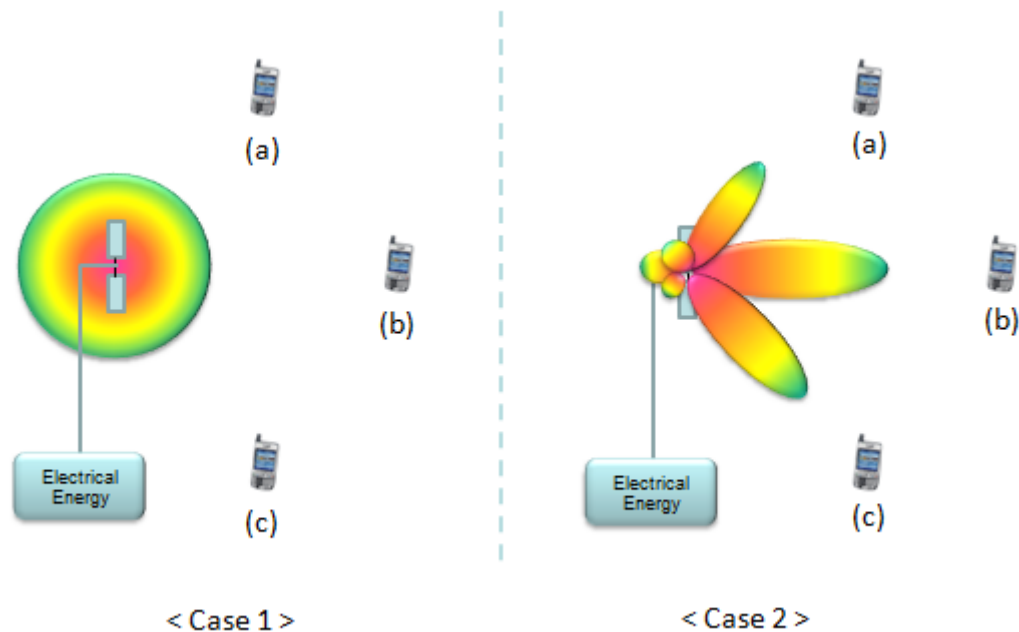


Figure 2.12: Comparison between Beam forming and Without Beam forming.

2.5.1 Beamforming Application

Applications	Description
Radar	Phased array Radar, Synthetic Aperture Radar.
Sonar	Under Water Source Location And Classification.
Communications	Directional Transmission and Reception, Smart Antenna System.
Imaging	Medical Diag,osis and Treatment using Tomography and Ultrasonic.
Geophysical Exploration	Seismic Arrays for Oil Exploration and Detection of Under Ground Nuclear Test.

Table 2.1: Application of beamforming technology.

2.5.2 Omni Directional VS Directional Antenna (smart)

Antenna is electrical device which converts electric power into electromagnetic waves. The antenna at the transmitter generates the radio wave. a voltage at the desired frequency is applied to the antenna. The voltage across the antenna elements and the current through them create the electric and magnetic waves, respectively. At the receiver, the electromagnetic wave passing over the antenna induces a small voltage. Thus, the antenna becomes the signal source for the receiver input. in current networks, antennas used in smart phones are broadcasted in all directions, energy will be scattered in all directions. Work has been developed for years when 5G is implemented in its use in phones similar to a beam of light that sends a beam of light (antennas) with wireless energy in a specific direction in when other directions are empty, the direction of the beam is controlled electronically or mechanically.

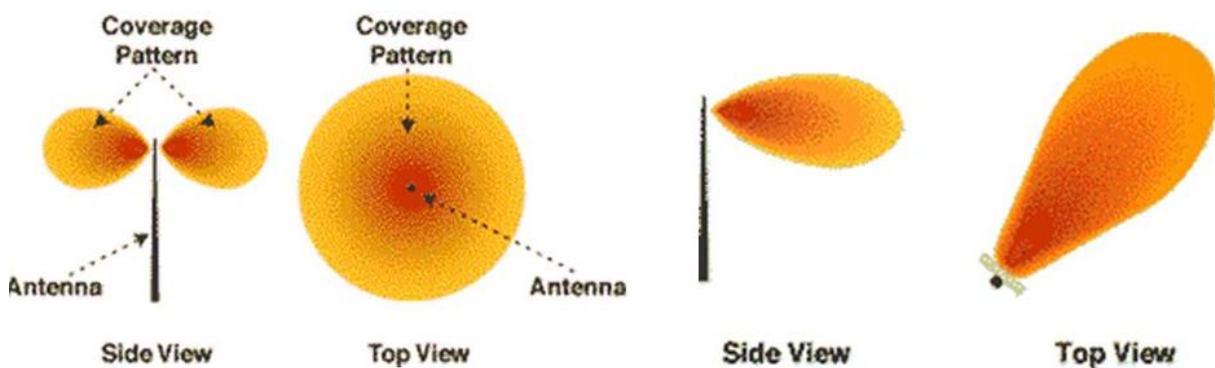


Figure 2.13: Regular Antenna VS Smart Antenna

2.5.3 Beam-forming in 5G

There will be a tower consisting of thousands of antennas, which is a large matrix, which may be from a one or 3 dimensions of arrays that are arranged in a certain geometric shape that allows a signal to be sent in certain directions based on the process of sensing the presence of a user in a specific direction, and then the antenna is directed this user as long as he By sending and receiving data after that, when the user stops sending and receiving data, this packet is routed again to another user , and so just as the same array is sending and receiving several packets of frequencies to a group of users, and of course this tower will be connected to the same LTE infrastructure that currently exists for 4G and be there is a match between 4G and 5G so That users who use 4G and 5G at the same time will be able to connect to the same towers so that users of the new systems will be able to use the old systems or vice versa figure 2.14.

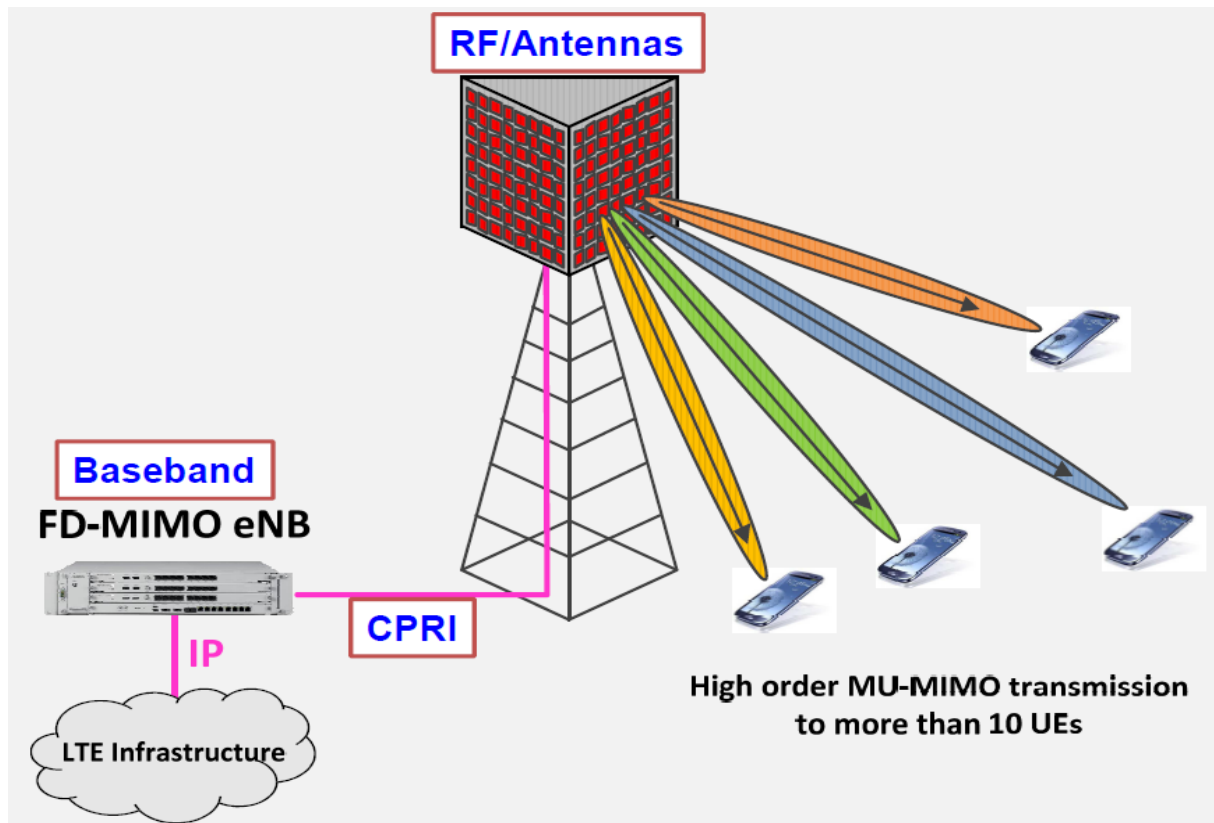


Figure 2.14: Beamforming in 5G.

2.5.4 for small devices antenna array on chip

An antenna array is assembled into a small chip if 41.6mm means 4cm in length and width. This contains a 256 element array chip that can be placed on one finger. The signal can be directed in a specific direction and prevented in the other directions using the so-called time delay. The second is transmitted at the moment 1, so whenever we change the time between the different antennas, the signal is directed in a certain direction that differs from the other direction, depending on the time difference between the different antennas. Beamforming is one of the technologies that will be strongly present in 5G communications, the official goal of which is to reduce energy consumption and overcome the main obstacle for Mm-waves, which is the short distance that it can cover.

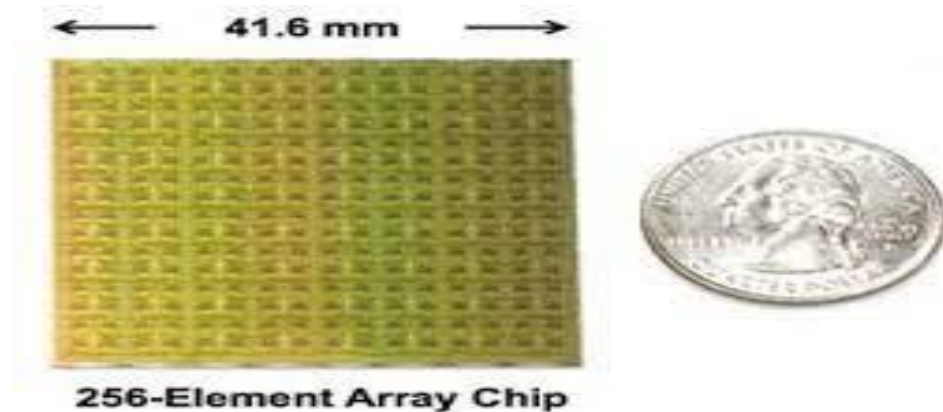


Figure 2.15: 256 Antenna Transmitter & receiver for high frequency.

2.5.5 Duplexing

Is the circulation mode used to transmit data both in the downlink “downlink” direction, therefore from the relay antenna to the user, and in the upstream “uplink” direction, therefore in the direction of the user, to the base station Figure 2.16.

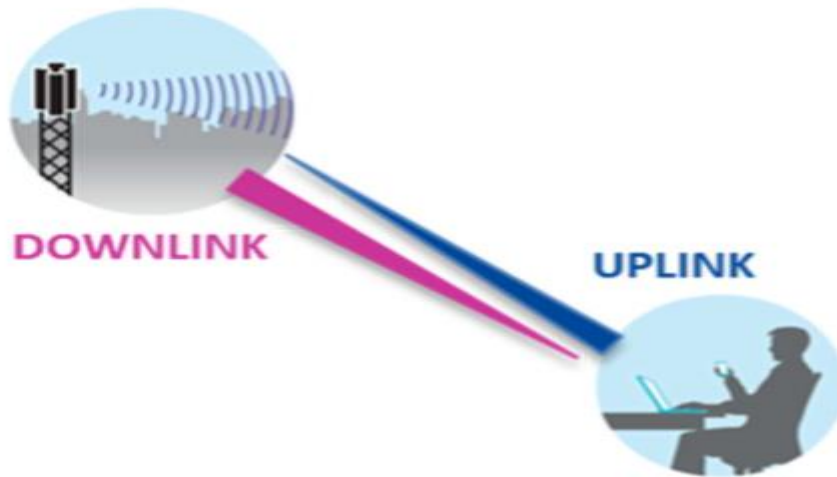


Figure 2.16: Echanges bilatéraux entre les antennes du réseau et les utilisateurs.

For 2G, 3G and 4G, frequency duplexing, called FDD (Frequency Division Duplexing), is used, this is a two-way traffic mode, each lane with its reserved frequency band. Frequency blocks are thus reserved for downlink transmissions and others for uplink transmissions Figure 2.17. In the frequency bands already allocated to mobile telephony, 5G will continue to use this FDD duplexing, which is based on frequency separation. however, data exchanges between the antennas of a mobile telephone network and mobiles now appear to be very largely unbalanced in the downstream direction (from antennas to mobiles). Indeed, on average, users receive much more data from the network (video, internet, downloading email) than they send (sending email). FDD mode is not flexible enough to accommodate this imbalance between downlink and uplink data flow.

In 5G, for the new open frequency bands, time-based duplexing, known as TDD (Time Division Duplexing), has thus been adopted Figure 2.17 in order in particular to make better use of all the available spectrum in the downstream direction. this is a one-way traffic mode with alternating traffic. The relay antennas and the terminals will therefore use the same frequency band but the direction of transmission will vary over time.

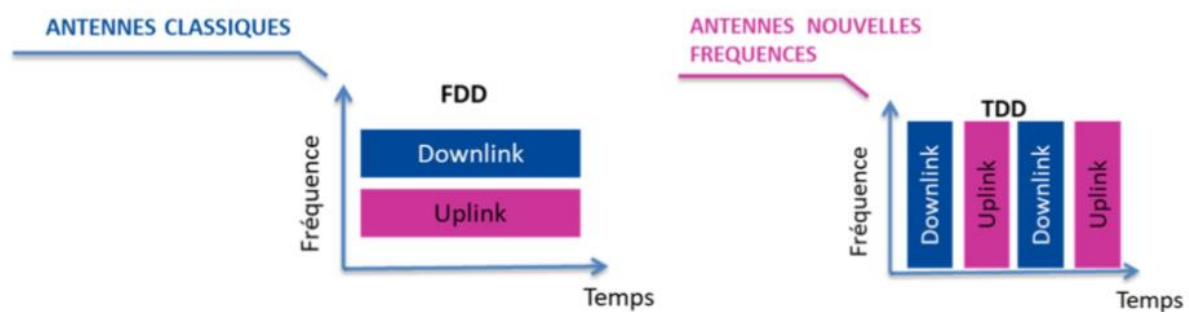


Figure 2.17: illustration of frequency (FDD) or time (TDD) duplexing.

The use of TDD time duplexing has the particular advantage of allowing great flexibility in downlink / uplink distribution; but it causes interference between antennas and between terminals which require specific techniques to be put in place to remedy it. Three main technical solutions are identified to allow the coexistence of several users operating TDD networks in adjacent frequency bands:

- Network synchronization which imposes a common transmission format on operators.
- The use of guard bands and specific filters by operator.
- Spatial separation of transmitters (geographic separation).

TDD time duplexing implies that during uplink periods, the antennas no longer transmit: the exposure due to the antennas in the network is therefore zero during these times.

2.5.6 Modulation

Data transmission between the network and the user is ensured by modulating the signal, that is, by encoding the information before sending it over the propagation channel. Multiplexing makes it possible to pass several information on the same transmission channel. Since the beginning of mobile telephony, different types of multiplexed modulation have been used Figure 2.18:

- **FDMA** “Frequency Division Multiple Access”: each user uses a dedicated frequency. FDMA was used in the early days of mobile telephony.
- **TDMA** “Time Division Multiple Access”: users all use the same frequency band but at different times. The distribution is done over time. 2G uses TDMA modulation, so mobiles only transmit one-eighth of the time in 2G.
- **CDMA** “Code Division Multiple Access”: the users all use the same frequency band simultaneously but with different codes which make it possible to distinguish them. 3G uses CDMA modulation.
- **OFMDA** “orthogonal frequency division multiple access”: the time / frequency matrix is divided into elementary resources which are distributed among the users. This modulation is used in 4G.

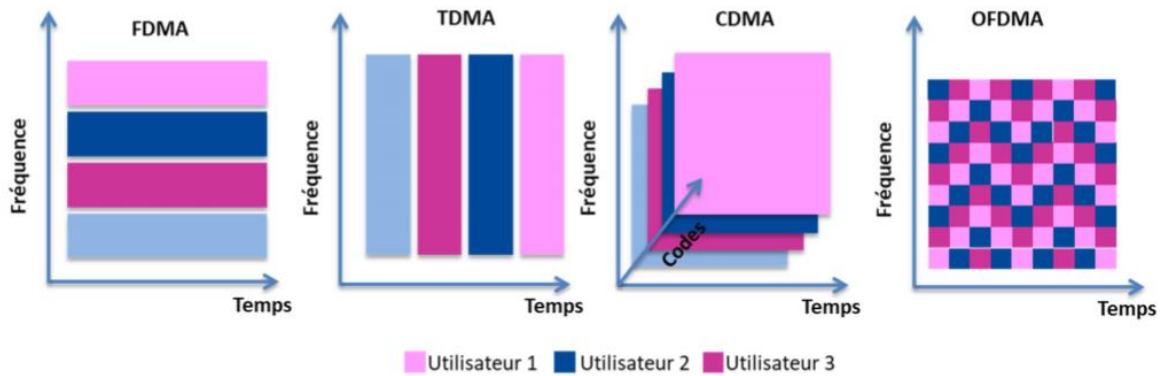


Figure 2.18: Information transmission standards between the user and the base station.

5G will be used like OFDMA's 4G, but with much more flexibility and flexibility in the time and frequency breakdown to allow users with a wide variety of constraints to be served Figure 2.19. it should be noted that OFDMA consists of simultaneously transmitting signals on several different carriers which results in high variability in instantaneous levels due to constructive and destructive interference. These constructive additions are measured by the PAPR ("Peak to Average Power Ratio") which is the ratio between the peak value and the average value of a signal.

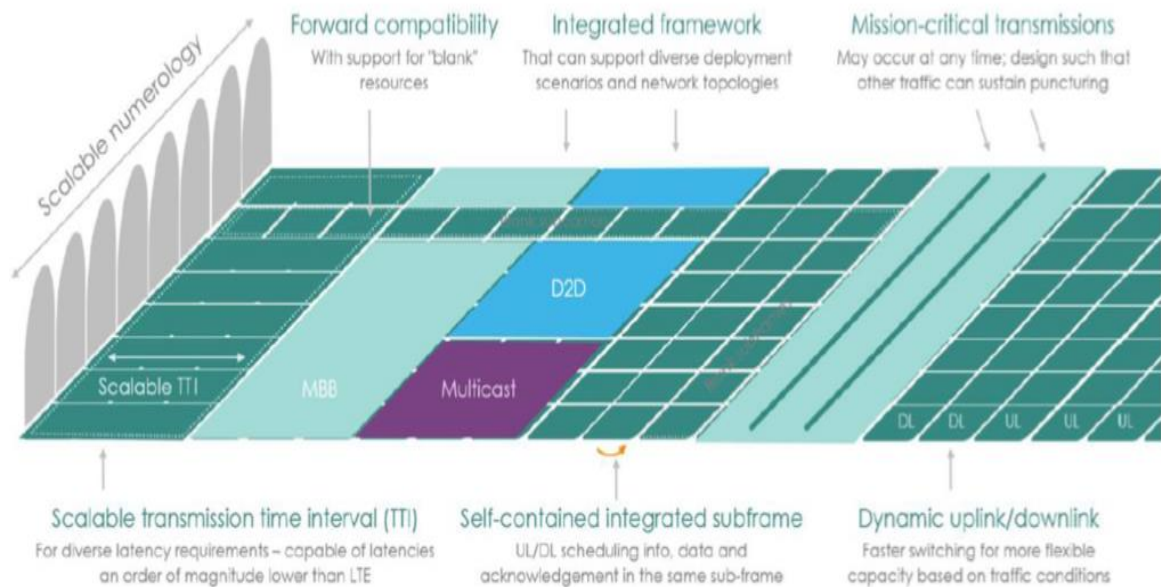


Figure 2.19: Distribution of resources in time and frequency to cover the different uses of 5G (eMBB, mMTC, uLLRC).

2.5.7 Types of Beamforming

Previously in 2G, 3G, 4G networks, there were a limited number of antennas in the base station so that it could be fully digital. The process of converting data from its original form to its high frequency transmission is done by digital or all in an analog way, except that in 5G networks It is planned that there will be hundreds or thousands of antennas in a very small area located in the base station or the main station, so it is very difficult to build them in analog or digital manner, so they had to what they called hybrid beamforming.

2.5.7.1 Analog beamforming

Analog beamforming is one of the simplest approaches for applying MIMO in mmWave systems it can be applied at both the transmitter and receiver, in conventional MIMO systems, each antenna element is connected to the baseband processor. This requires a dedicated mixer, analog-to-digital converter (ADC) or digital to-analog converter (DAC), The series of the components that connect the antennas to the baseband are called radio frequency (RF) chains, it means the signal that comes to us, whether it is (audio, image, video) or any kind of signals that we want to send, we insert it into a digital baseband or a precoder that converts the signal from its original form into digital forms. After that, we will insert it into a group of phase shifters. The one that will determine the direction of this data will then enter a group of antennas, each one of these phase shifters is connected to this antenna and is characterized by its poor-resolution analog beamforming because these phase shifters are always limited in resolution and do not achieve things that can be achieved with digital only.

- Also known as Single-port beamforming.
- Beam former has no knowledge of signals on individual antenna-elements.
- For analog data approaches like gradient based Perturbation algorithm are used to update weight.
- Economical as a only one RF down converter and ADC is used.

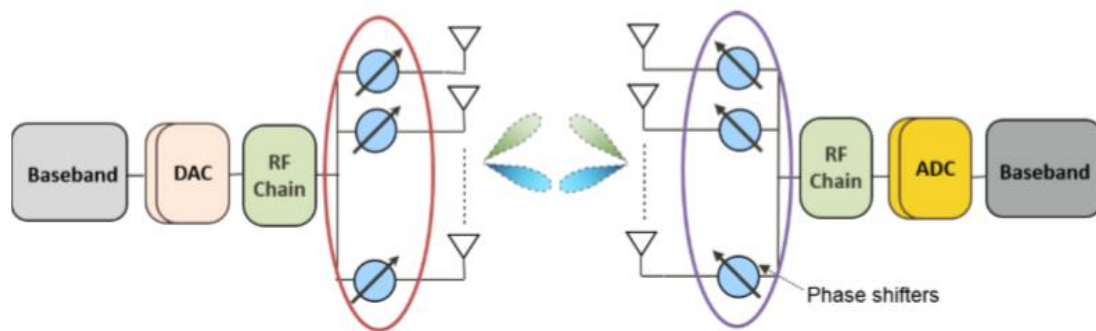


Figure 2.20: MmWave MIMO system using analog only beamforming.

2.5.7.2 Digital Beamforming

We have a digital baseband, which is a precoder through which we can control the amount and direction of the signal here. We achieve very high accuracy and thus we will obtain through it the phase efficiency or the frequencies used are very large. The number of antennas is very large, therefore if we place the RF chain for each one of these antennas completely digital, digital baseband, its size will be too large to accommodate the small area of the mmwave antennas, therefore there will be a large energy consumption and a large heat emission that may lead to burning this base station, so it became difficult to put an antenna in one board and make them all digital. At the same time, we do not want to leave them all analog. As we mentioned earlier, the accuracy is very weak. We cannot perfectly direct the data in narrow packages without much errors.

- Also known as Multiport Beamforming.
- Beam-former can access signals on all antenna-elements.

- For digitally sampled data, approaches like conjugate-gradient and Least-square are used for better convergence speed of beamforming algorithms.
- Not very economical as one RF down converter and ADC has to be used at each antenna element.

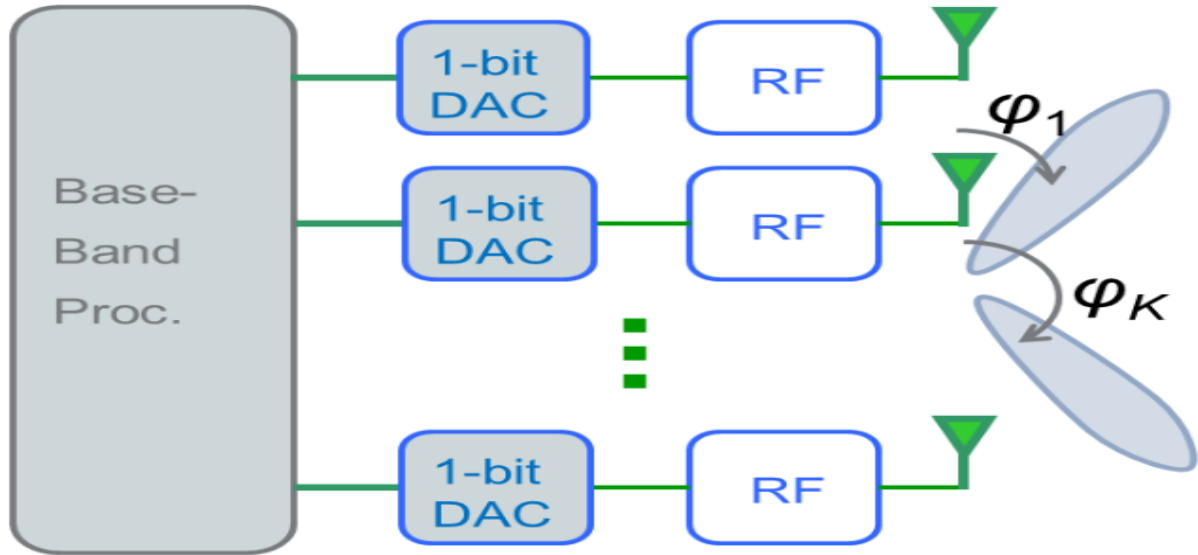


Figure 2.21: MmWave MIMO system using Digital only beamforming.

2.5.7.3 Hybrid Beamforming

The ideal mmWave massive MIMO hardware realization requires number of RF chains equal to the number of antennas. The RF chain consists of hardware components such as ADC/DAC, mixer, etc. On the other hand mmWave wireless channel does not encourage multipath reflections and offers a sparse channel between TX and RX. These two conditions motivates the design of hybrid beamforming with the number of RF chains as low as the required data streams. The increase of energy consumption in massive MIMO antennas technology adopted for 5G wireless communication systems is mainly due to the large number of antennas and RF chains. Large antenna arrays will be intensively used in the future mmWave cellular networks, and different possible antenna architectures and MIMO techniques will be needed. Instead of implementing a fully digital beamforming, which requires one distinct RF chain for each antenna, a two-stage hybrid linear precoding and combining scheme is a possible solution. In contrast to centimeter wave (Cm-Wave) communication systems which make the use of large antenna arrays at either TX or RX or both to have sufficient link margin, the mmWave communication systems are much more compact and require fewer spatial degrees of freedom for parallel multi-stream transmission [18]. Hybrid analog and digital beamforming is an emerging technique for large-scale MIMO systems since it can reach the performance of the conventional fully digital beamforming schemes, with much lower hardware implementation complexity and power consumption. The green design of the RF chains, the use of simplified TX/RX structures, and the energy efficient design of power amplifiers are among the hardware solutions to improve the EE, especially in systems with many antennas such as massive MIMO systems and mmWave systems. Hybrid analog and digital beamforming structures have been proposed to lower

energy consumption for mmWave communications [19]. Digital beamforming offers better performance at increased complexity and cost. In contrast, the analog beamforming is a simple and cost effective method with less flexibility. The Hybrid beamforming architecture provides sharp beams with phase shifters (PSs) at analog domain and flexibility of digital domain [20]. The vulnerability to blocking and the need for strong directionality are the most important physical challenges for mmWave cellular systems. The authors of [21], review mathematical models for mmWave cellular systems and analyze the fundamental physical differences from conventional Sub-6GHz cellular systems. The need for significant directionality at the TX and/or RX, is achieved through the use of large antenna arrays of small individual elements [21]. A fully-digital processing is hard to realize at mmWave frequencies with wide bandwidths and large antenna arrays, because the baseband precoding/combining processing assumes that the transceiver dedicates an RF chain per antenna as shown in Fig 2.25. An analog beamforming can be implemented using networks of phase shifters as shown in Fig 2.24, but it consumes high power and cannot provide the data streams multiplexing. The hybrid precoding architecture in Fig 2.26, provides a flexible compromise between hardware complexity and system performance[21]. The hybrid beamforming structure are proposed as an enabling technology to obtain the benefits of MIMO and also to provide high beamforming gain to overcome the high propagation loss in mmWave bands, for 5G cellular communications [22].

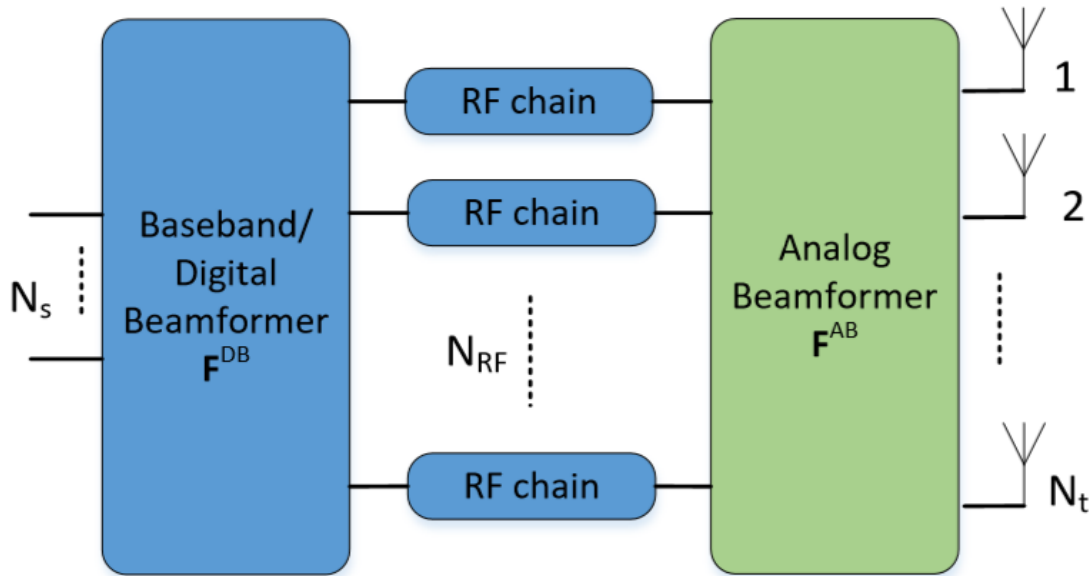


Figure 2.22: Hybrid analog/digital architecture.

2.5.7.3.1 Fully-connected and Sub-connected Hybrid Beamforming Structures

In a fully-connected hybrid beamforming structure, each RF chain is connected with all antennas, and the transmitted signal on each of the N_{RF} digital transceivers goes through N_{RF}^t paths (mixer, power amplifier, phase shifter, etc.) and summed up before being connected with each antenna see Fig 2.27. In sub-connected or partially connected structure each of the N_{RF} RF chain is connected to N_t/N_{RF} number of sub-arrays as shown in Fig 2.28. The fully-connected structure provides full beamforming gain per transceiver but has a high

complexity of $N_{RF} \times N_t$ RF paths. On the other hand, sub-connected has lower hardware complexity of N_{RF}^t paths at the cost of $1/N_{RF}$ beamforming gain compared with fully-connected structure. The sub-connected structure is more practical for UEs in uplink because of stringent power constraints at handheld terminals. In general, a smaller transceiver number N_{RF} brings more EE performance improvement with a given SE reduction. Thus the combination of massive MIMO systems with hybrid beamforming structure including a much reduced transceiver number, is expected to bring significant EE and SE enhancement to 5G. In the fully-connected hybrid beamforming, each RF chain is connected to N_t PSs, hence, there are $N_{RF}N_t$ PSs. In the sub-connected hybrid beamforming, each RF chain is connected to a subset (N_t/N_{RF}) of PSs, hence, there are N_t number of PSs. The fully-connected structure provides gain of $N_{RF}\log_2(N_{RF})$ in SE over the sub-connected, but at the expense of N_{RF} times more power consumption [23].

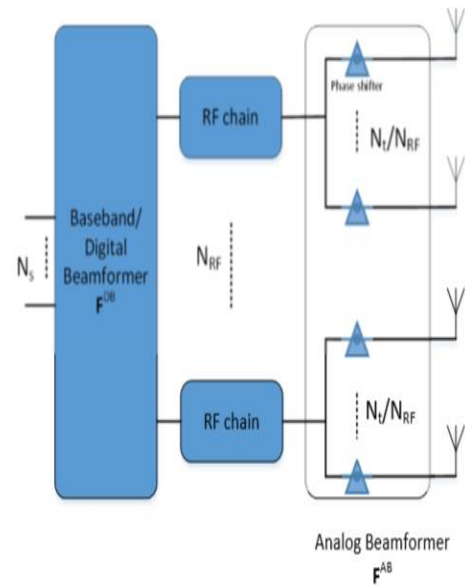
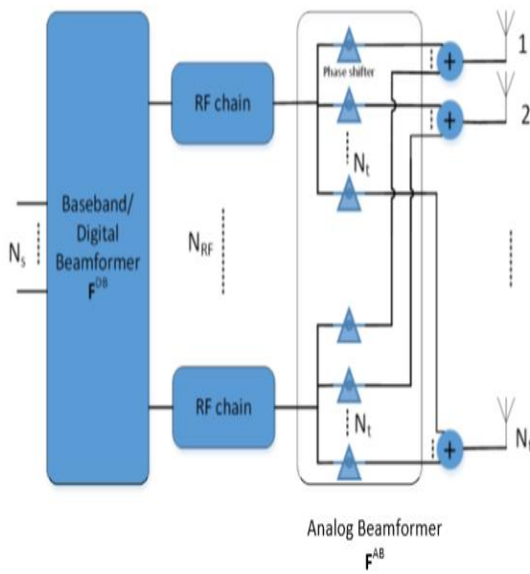


Figure 2.23: Fully connected hybrid beamforming. **Figure 2.24:** Sub-connected hybrid beamforming.

2.5.7.3.2 Hybrid beamforming system

Hybrid beamforming in mm-Wave massive MIMO systems has been studied by the 5G research community in various combinations of transmit/receive number of nodes and the number of antennas. In the hybrid beamforming, a signal is first digitally precoded by a baseband precoder, passes through the RF chain (ADC/DAC, data converter, mixer), there are N_T antennas in transmitter and N_R antennas in receiver. The transmitter can send N_s streams to the receiver with N_t^{RF} RF chains and DACs, in the transmitter, baseband precoder using digital signal processing and constrained RF precoder using RF phase shifters are implemented. Similarly, RF combiner and baseband combiner are implemented in the receiver.

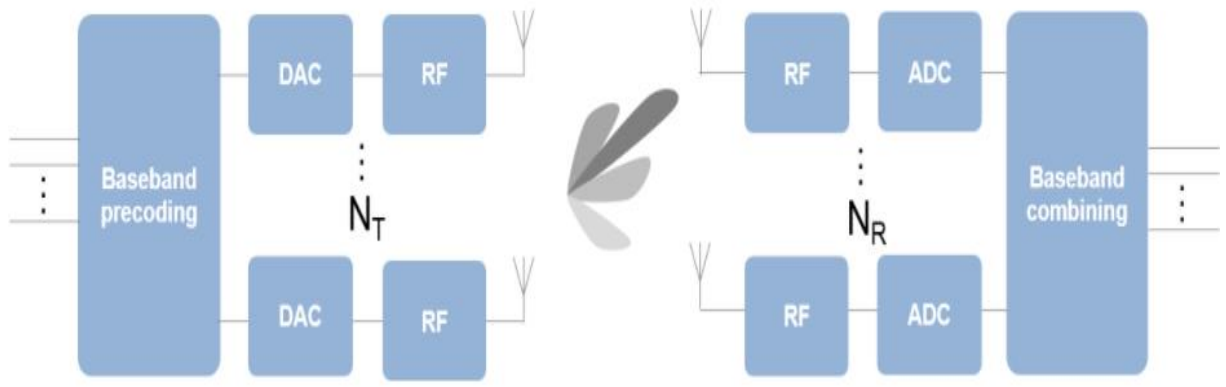


Figure2.25: Hybrid beamforming system.

If N_s is equal to N_t^{RF} , the transmitter becomes an analog beamformer. The same is true of the receiver. I we only consider the hybrid beamformer with following conditions.

$$\begin{aligned} N_s < N_t^{RF} < N_t \\ N_s < N_r^{RF} < N_r \end{aligned} \quad (2.2)$$

Equation2.2:the conditions of Hybrid beamforming.

The transmitter has an $N_t^{RF} \times N_s$ baseband precoder F_{BB} , followed by an $N_t \times N_t^{RF}$ RF precoder F_{RF} . The transmit signal is presented as follows:

$$X = F_{RF} F_{BB} s. \quad (2.3)$$

Equation2.3:The transmit signal.

Where : X is $N_t \times 1$ vector and s is the $N_s \times 1$ stream vector such that:

$$E[ss^H] = I_{N_s} / N_s. \quad (2.4)$$

Equation2.4:The analog beamformers.

Since the RF precoder is equipped with analog phases hifters. The analog beamformers are unitary matrices with equal-norm elements i.e:

$$[[F_{RF}]_{:,i} [F_{RF}]_{:,i}^H], i = 1/N_t \quad (2.5)$$

Equation2.5:equal-norm elements.

And we have power constraint on the transmitter as:

$$\|F_{RF} F_{BB}\|_F^2 = N_s. \quad (2.6)$$

Equation2.6:The total power constraint.

We assume the H as a narrowband block-fading propagation channel, and both transmitter and receiver have perfect channel state information (CSI). Therefore, we can represent the received signal as follows:

$$y = \sqrt{\rho} Hx + n$$

$$y = \sqrt{\rho} H F_{RF} F_{BB} s + n. \quad (2.7)$$

Equation2.7:the received signal.

where y is the $N_r \times 1$ vector, H is the $N_r \times N_t$ channel matrix which satisfies $E\{|H|^F\} = N_r N_t$, ρ is the average received power, and n is the $N_r \times 1$ vector of $CN(0, \sigma_n^2)$ noise. At the receiver, the RF combiner W_{RF} and the baseband combiner W_{BB} are used to recover the transmitted data stream s from the received signal y . After combining, the received stream s can be written as:

$$s = W_{BB}^H W_{RF}^H y.$$

i.e:

$$s = \sqrt{\rho} W_{BB}^H W_{RF}^H H F_{RF} F_{BB} s + W_{BB}^H W_{RF}^H n. \quad (2.8)$$

Equation2.8:the received stream.

Where W_{RF} is the $N_r \times N_r^{RF}$ matrix with unit norm entries is the analog combiner, and W_{BB} is the $N_r^{RF} \times N_s$ is the baseband combiner matrix.

By assuming that the Gaussian symbols are transmitted through the mmWave channel, we can define the spectral efficiency achieved by the hybrid beamforming as:

$$R^{HYB} = \log_2(|I_{Ns} + \rho/N_s \Lambda_n^{-1} W_{BB}^H W_{RF}^H H \times F_{RF} F_{BB} F_{BB}^H F_{RF}^H H^H W_{RF} W_{BB}|). \quad (2.9)$$

Equation2.9:the spectral efficiency.

Where:

$$\Lambda_n = \sigma_n^2 W_{BB}^H W_{RF}^H W_{RF} W_{BB}. \quad (2.10)$$

Equation2.10:the covariance matrix.

is the covariance matrix of the noise after combining in this work is to estimate the hybrid beamformers F_{RF} , W_{RF} , F_{BB} and W_{RF} that maximize the spectral efficiency.

2.5.7.3.3 Channel Model

The channel matrix H is composed of N_{cl} clusters which are distributed uniformly in space, and N_{ray} rays have a truncated Laplacian distribution in each cluster [12]. Using this model, the channel matrix H can be written as:

$$H = \gamma \sum_{i=1}^{N_c} \sum_{j=1}^{ray} \alpha_{ij} g_R(\theta_R^{(ij)}) g_T(\theta_T^{(ij)}) a_R(\theta_R^{(ij)}) a_T^H(\theta_T^{(ij)}). \quad (2.11)$$

Equation2.11:the channel matrix.

where :

- $\theta_R^{(ij)} = (\varphi_R^{(ij)}, \theta_R^{(ij)})$: the angle of arrivals.
- $\theta_T^{(ij)} = (\varphi_T^{(ij)}, \theta_T^{(ij)})$: angle of departures.

the angular parameters φ and θ as the azimuth and the elevation angles respectively.

$$\gamma = \sqrt{N_T N_R / (N_c N_{ray})}. \quad (2.12)$$

Equation 2.12: the normalization factor.

- α_{ij} : the complex channel gain associated with the i th scattering cluster and j th path for:
 $i = 1, \dots, N_c$ and $j = 1, \dots, N_{ray}$.
- $g_R(\theta_R^{(ij)})$: the antenna element for receive.
- $g_T(\theta_T^{(ij)})$: the antenna element for transmit.
- $a_R(\theta_R^{(ij)})$: are $N_R \times 1$ steering vectors representing the array responses at the receiver.
- $a_T^H(\theta_T^{(ij)})$: are $N_T \times 1$ the array responses at the transmitters.

The n th element of the steering vector $a_R(\theta_R^{(ij)})$ is given as :

$$[a_R(\theta_R^{(ij)})]_n = \exp\{-2\pi/\lambda P_n^T r(\theta_R^{(ij)})\}.$$

Where :

$P_n = [x_n, y_n, z_n]^T$: is the position of the n th receive antenna in Cartesian coordinate system.

$$(\theta_R^{(ij)}) = [\sin(\varphi_R^{(ij)})\cos(\theta_R^{(ij)}), \sin(\varphi_R^{(ij)})\sin(\theta_R^{(ij)}), \cos(\theta_R^{(ij)})]^T.$$

- $a_T(\theta_T^{(ij)})$: The transmit side steering vector.
- $a_R(\theta_R^{(ij)})$: The response side steering vector.

2.5.7.3.4 HYBRID PRECODER/COMBINER DESIGN

2.5.7.3.4.1 Precoder Design

In digital beamforming systems, the singular value decomposition (SVD) of H can be used to design the precoder and combiner, and we consider the right singular vectors as the optimal precoder F^{opt} . In hybrid beamforming systems, F^{opt} cannot be implemented due to the hardware constraints. The precoding algorithm is proposed by solving the optimization problem which is to find the best low dimensional presentation of F^{opt} using the basis vectors at (φ_k, θ_k) , $1 \leq k \leq N_{cl}N_{ray}$. This algorithm is based on the well known concept of basis pursuit and the pseudo-code.

2.5.7.3.4.2 Combiner Design

The combining algorithm is similar to the precoding algorithm. Note that when we design both precoder and combiner, it is better to start at the side with less RF chains, i.e. the more constrained side. For example, consider the case where a receiver only has a single RF chain and thus is restricted to applying a single response vector $a_r(\varphi_1^r, \theta_1^r)$. In such a situation, separately designing the precoder to approximate F^{opt} and radiate power in several directions leads to a loss in actual received power (since the receiver can only form a beam in one direction). As a result, the transmitter must always consider the constraints at the receiver.

2.5.7.3.5 Hybrid Beamforming Design

The optimization problem for joint estimation of hybrid beamformers $F_{RF}, F_{BB}, W_{RF}, W_{BB}$, can be stated as follows :

$$F_{RF} \in F_{RF}, W_{RF} \in W_{RF},$$

$$\|F_{RF} F_{BB}\|_F^2 = N_S,$$

We first define the sets F_{RF} and W_{RF} . Note that the analog beamformers F_{RF}, W_{RF} are related with the array responses $a_T(\Theta_T^{(ij)})$, $a_R(\Theta_R^{(ij)})$ through linear transformation. Hence the feasible RF beamformer sets can be formed as:

$$F_{RF} = \{F_{RF}^{(1)}, \dots, F_{RF}^{(Q_F)}\} \text{ where } F_{RF}^{(q_F)} = a_T(\Theta_T^{(ij)}), i=1, \dots, N_c, j=1, \dots, N_{ray}$$

- $Q_F = \binom{N_{path}}{N_{RF}^{RF}}$: is the number RF precoder candidates, $q_F = 1, \dots, Q_F$.
- $N_{path} = N_c N_{ray}$: The feasible set for RF combiner is similarly defined as :

$$W_{RF} = \{W_{RF}^{(1)}, \dots, W_{RF}^{(Q_W)}\} \text{ where } W_{RF}^{(q_W)} = a_R(\Theta_R^{(ij)}), i=1, \dots, N_c, j=1, \dots, N_{ray}.$$

$Q_W = \binom{N_{path}}{N_{RF}^{RF}}$, Now we can present the joint precoder and combiner design problem as follows :

$$q_F, q_W = \arg \max \log_2(|I_{N_s} + \frac{\rho}{N_s} \Lambda_n^{-1} W_{RF}^H W_{BB}^H \times H F_{RF} F_{BB} F_{BB}^H F_{RF}^H H^H W_{RF} W_{BB}|). \quad (2.13)$$

Equation2.13: the joint precoder and combiner design.

$$\text{s.t: } F_{RF} = F_{RF}^{(q_F)}, W_{RF} = F_{RF}^{(q_F)}, F_{BB} = (F_{RF} F_{RF})^{-1} F_{RF}^H F_{opt},$$

$$W_{BB} = (W_{BB}^H \Lambda W_{RF})^{-1} (W_{RF}^H \Lambda W_{opt}),$$

Where :

- q_F, q_W : represent the selected elements in the feasible sets.

$$\Lambda = \frac{\rho}{N_s} H F_{RF} F_{BB} F_{BB}^H F_{RF}^H H^H + \sigma_n^2 I_{N_{RS}}. \quad (2.14)$$

Equation2.14: the covariance of the array output.

- F_{opt} and W_{opt} : are the optimum baseband beamformers which can be obtained from the singular value decomposition (SVD) of the channel matrix.
- $U \in N_R \times \text{rank}(H)$, $V \in N_T \times \text{rank}(H)$: the left and the right singular value matrices of H .

Where :

the SVD of $H \in N_R \times N_T$ is $H = U \Sigma V^H$.

- Σ : is $\text{rank}(H) \times \text{rank}(H)$ matrix composed of the singular values of H .

By decomposing Σ and V as :

$$\Sigma = \text{diag}\{\Sigma(1), \Sigma(2)\}, V = [V(1), V(2)].$$

Where :

$$V(1) \in N_T \times N_S, V(2) \in N_T \times N_R - N_S.$$

select the unconstrained precoder as $F_{\text{opt}} = V(1)$. Using the unconstrained beamformer F_{opt} , W_{opt} can be computed as :

$$W_{\text{opt}} = \left(\frac{1}{\rho} (F_{\text{opt}}^H H^H H F_{\text{opt}} + \frac{N_S \sigma_n^2}{\rho} I_{N_S})^{-1} F_{\text{opt}} H H^H \right)^H. \quad (2.15)$$

Equation 2.15: the optimum baseband beamformers.

The solution of (2.13) requires $Q_F Q_W$ nodes. In order to reduce the complexity, is decomposed into two different problems where precoders (F_{RF} and F_{BB}) and combiners (W_{RF} and W_{BB}) are separately estimated. the complexity is reduced from $Q_F Q_W$ to $Q_F + Q_W$. In order to find the precoders we solve the following problems :

$$q_F = \arg \max \log_2 \left(\left| I_{N_S} + \frac{\rho}{N_S \sigma_n^2} (W_{\text{opt}}^H H W_{\text{opt}})^{-1} W_{\text{opt}}^H \times H F_{\text{RF}} F_{\text{BB}} F_{\text{BB}}^H F_{\text{RF}}^H H^H W_{\text{opt}} \right| \right). \quad (2.16)$$

Equation 2.16: Precoder design.

$$\text{s.t: } F_{\text{RF}} = F_{\text{RF}}^{q_F}, F_{\text{BB}} = (F_{\text{RF}}^H F_{\text{RF}})^{-1} F_{\text{RF}}^H F_{\text{opt}}.$$

$$q_W = \arg \max \log_2 \left(\left| I_{N_S} + \frac{\rho}{N_S \sigma_n^2} (W_{\text{BB}}^H W_{\text{RF}}^H H W_{\text{RF}} W_{\text{BB}} W_{\text{BB}}^H W_{\text{RF}}^H)^{-1} H F_{\text{opt}} F_{\text{opt}}^H H^H W_{\text{RF}} W_{\text{BB}} \right| \right). \quad (2.17)$$

Equation 2.17: Combiner design.

$$\text{s.t: } W_{\text{RF}} = W_{\text{RF}}^{(q_W)},$$

$$W_{\text{BB}} = (W_{\text{RF}}^H \Lambda W_{\text{RF}})^{-1} (W_{\text{RF}}^H \Lambda W_{\text{opt}}^H),$$

$$\Lambda = \frac{\rho}{N_S} H F_{\text{opt}} F_{\text{opt}}^H H^H + \sigma_n^2 I_{N_R}.$$

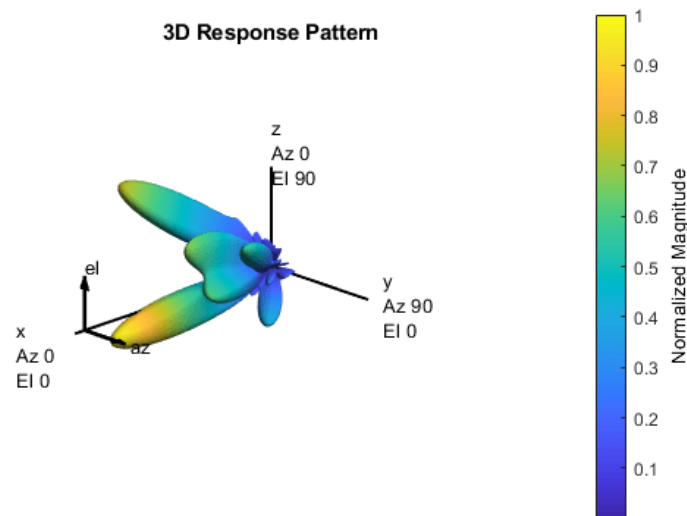


Figure 2.26: The beamforming pattern of the hybrid weights.

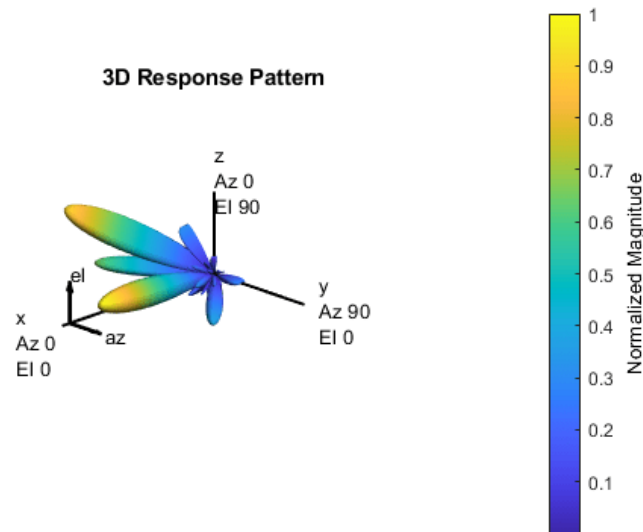


Figure 2.27: the beamforming using the optimal weights.

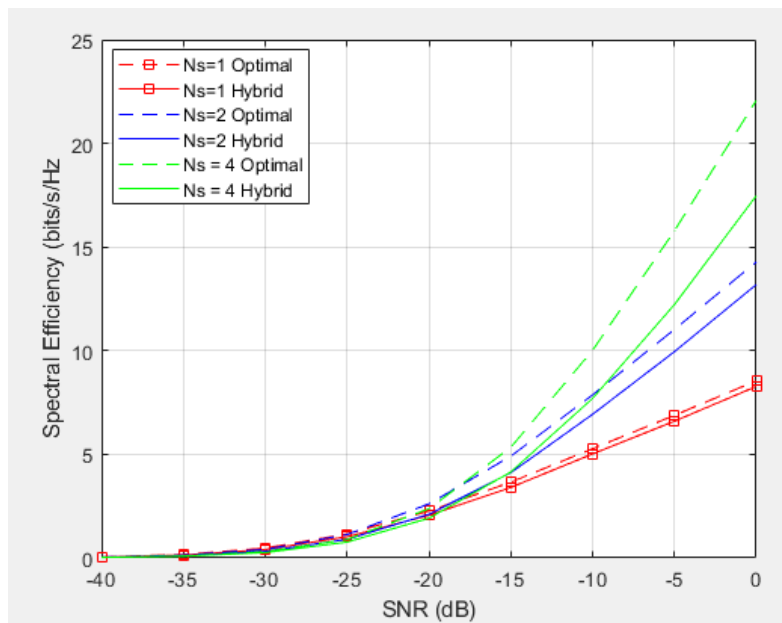


Figure 2.28: the spectral efficiency.

2.6 The related works

Classification of the Related Work on the Basis of hybrid beamforming are given in Table 2.3

Paper	Solution Method	Analog RF matrix	Digital RF matrix	RF chains	SE Performance matrix
Alkhateeb et al.	Switch-based combining.	Quasi-coherent combining.	1	$K \leq N_{RF} < N_r$	2.8bps /Hz at 0dB with $K=3, N_{RF}^{rx} = 3$ $N_t = 1, N_r = 64$
Li et al.	Reduce inter user interference.	Gram-Schmidt method.	MMSE beamforming.	BS : $K = N_{RF} < N_r$	50bps /Hz at 0db with $K=4, N_t = 32$, $N_{RF}^{rx} = 1, N_r = 128$ $N_{RF}^{tx} = 4$
Gao et al.	Distributed grid matching pursuit.	Iterative algorithm in angular domain.	Iterative algorithm in angular domain	BS : $K = N_{RF} < N_r$ UE : $1 = N_{RF} < N_t$	8.8bps/Hz at 0db $k=4, N_{RF}^{rx} = 4$, $N_t = 32, N_r = 128$ $N_{RF}^{tx} = 1$
Noh et al.	Kalman filter based channel estimation and Toeplitz distribution theorem for hybrid beamforming .	Toeplitz matrix decomposition by DFT matrices.	Toeplitz matrix decomposition by DFT matrices.	$1 < N_{RF} < N_t$	6bps/Hz at 0db with $K=5, N_t = 32$
Ni et al.	Hybrid block diagonalization .	Equal gain transmission method.	Block diagonalization of effective channel.	BS : $k N_s < N_{RF} < N_t$ UE : $k N_s < N_{RF} < N_r$	80bps/Hz at 0db with $K=8, N_t = 256$, $N_r = 16$
Jiang et al.	Joint radio resource allocation and hybrid beamforming.	N_{RF} column vectors selection from quantized codebook.	Weighted MMSE.	$N_s \leq k \leq N_{RF} \leq N_t$	10.15bps /Hz at -10db With $N_t = 512, N_{RF}^{tx} = 2, k=2$.
Nguyen et al.	OMP .	Transmit array response vectors assuming perfect AoD Knowledge.	For known F^{AB} , minimize the sum-MSE .	$k \leq N_{RF}$	38bps /Hz at 0db With $N_t = 64$, $N_r = 16, k = N_{RF} = 8$.
Amadori et al .	Beamspace MIMO and beam selection .	Beam selection algorithms with discrete lens array .	K dimensional ZF precoder .	$N_{RF} = K$	1.3bps/Hz , at .dB with $N_t = 81$, discrete lens array, selected antennas sub-set $N=40$, $K=40$.
Zi et al .	Minimize the Euclidean distance between optimal precoder and hybrid precoder .	Iterative algorithms to find N_{RF} column vectors from steering matrix.	Iterative algorithm to find N_{RF} rows matrix .	$k < N_{RF} < N_t$	35bps/Hz at $P_t = 33\text{dBm}$ with $N_t = 200, K = N_{RF} = 10$, $L=30$.
Liu et al.	CodeBook –based hybrid beamforming .	Semidefinite relaxation and fairness-aware greedy algorithm.	Linear precoding on effective channel.	$k = N_{RF} < N_t$	42bps/Hz at 0dB with $N_t = 64, K = N_{RF} = 10$.
Fujio et al.	Inter leaved subarray beamforming.	Weighted array manifold vectors .	Linear precoding on effective channel.	$k \leq N_{RF} < N_t$	5bps/Hz at 0dB with $N_t = 16, K=2$.

Table 2.2: the Related Work on the Basis of hybrid beamforming.

Paper	Solution Method	Analog RF matrix	Digital RF matrix	RF chains	SE Performance matrix
Brady et al.	Continuous aperture Phased-MIMO.	Discrete lens array via Butler matrices.	Conventional digital beamforming for reduced dimensional orthogonal beams.	$N_{RF} < N_t$	40bps /Hz at 0dB with 676*676 , $N_{RF}=4$, Discrete lens array.
Mai et al.	Minimizing the Euclidean distance between the hybrid precoder and the optimal minimum MSE precoder.	Jacobi algorithm on simultaneous matrix diagonalization problem.	Unconstrained baseband precoder via effective channel.	BS : $N_s \leq N_{RF} < N_t$ UE : $N_s \leq N_{RF} \leq N_r$	Not available .
Phyo et al.	Zero forcing beamforming algorithm.	Monte-Carlo simulation for rate maximization.	Monte-Carlo simulation for rate maximization.	BS : $N_{RF} < N_t$, UE : $N_s = N_{RF} \leq N_t$	20bps/Hz at 0db 120*60, $N_{RF}^r = 8$, $N_{ray} = 3, N_{RF}^{tx} = 16$
Zochmann et al.	Compress sensing based channel estimation and beamforming .	N_{RF} array response vectors.	Optimal combination of array response vectors.	BS : $N_{RF} < N_t$ UE : $N_{RF} < N_r$	10bps/Hz at 0db with 64*16, $N_{RF}^{tx} = 16$ $N_{RF}^r = 8$.

Table 2.2: the Related Work on the Basis of hybrid beamforming.

2.7 Conclusion

Through our study of the technologies used in the fifth generation and its architecture, it was found that they are completely different from the architecture of previous generations, especially the fourth generation of them, as they are very complex and expensive. where the fifth generation architecture depends on Mm Wave, Massive MIMO, Small Cell, Beamforming and The Full duplex.

CHAPTER III

**Deep learning for 5G MIMO hybrid
precoding and combining design**

3.1 Introduction

With the move to 5G, 5G networks will see the deployment of an order of magnitude with more cells (interlaced into the existing fabric of 4G LTE macro-cells) and antennas (both passive and active ones that utilize multiple frequencies). 5G will also allow for the introduction of other technologies to handle a huge increase in capabilities, with an emphasis on enabling the ultra-low-latency data transmission that 5G is designed for. Such a complex network requires a simplified solution, and deploying artificial intelligence (AI) and machine learning (ML) to solve these problems, compared to the conventional methods, machine learning (ML) is more powerful to uncover the inherent characteristics inside data/signals collected in an end-to-end manner and thus can achieve better performance when addressing various problems in wireless communications. Deep learning (DL) has been successfully used in joint channel estimation and signal detection of OFDM systems with interference and non-linear distortions .where denoising neural network (NN) is used in each iteration to update the estimated channel. In this these, we use the deep convolutional NN (CNN) to address channel estimation for mm-Wave massive MIMO OFDM systems.

3.2 What is machine learning?

Machine learning is a branch of artificial intelligence (AI) and computer science which focuses on the use of data and algorithms to imitate the way that humans learn, gradually improving its accuracy. Machine learning is an important component of the growing field of data science. Through the use of statistical methods, algorithms are trained to make classifications or predictions, uncovering key insights within data mining projects. These insights subsequently drive decision making within applications and businesses, ideally impacting key growth metrics. As big data continues to expand and grow.

3.3 What is Deep learning?

Is a subfield of machine learning, which is based on computers processing large amounts of data using artificial neural networks whose structure mimics that of the human brain. Whenever new information is incorporated, the existing connections between neurons are subject to change and expand, which has the effect of allowing the system to learn things without human intervention, autonomously, while improving the quality of its decision-making and forecasts.

3.3.1Deep Learning vs Machine Learning

Machine learning and deep learning are part of artificial intelligence see figure3.1. These approaches both result in empowering computers to make intelligent decisions. However, deep learning is a subcategory of machine learning because it relies on unattended learning. Machine learning is the oldest and simplest technology. It is based on an algorithm which adapts itself to the system based on human feedback. The implementation of this technology implies the existence of organized data. The system is then fed with structured and categorized data allowing it to understand how to classify new, similar data. Deep learning doesn't need structured data. The system works from several layers of neural networks, which combine different algorithms taking inspiration from the human brain. Thus, the system is able to work from unstructured data.

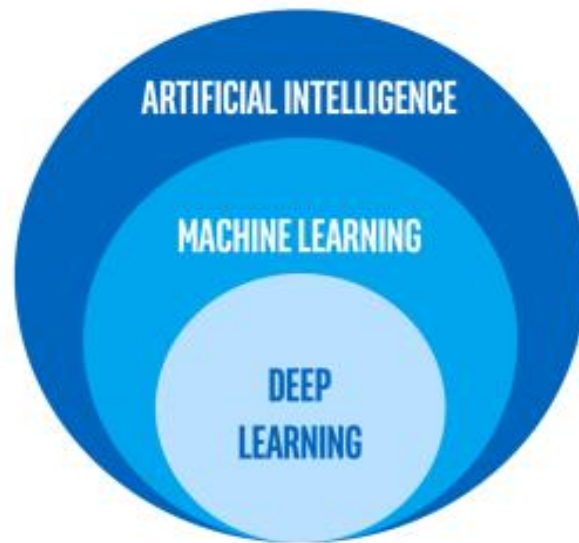


Figure 3.1:The relation between AI, ML, DL.

MACHINE LEARNING	DEEP LEARNING
Optimal data volumes	
Thousands of data points	Big data: millions of data points
Outputs	
Numerical value, like classification or score	Anything from numerical values to free-form elements, such as free text and sounds
How it works	
Uses various types of automated algorithms that learn to model functions and predict future actions from data	Uses neural networks that pass data through many processing layers to interpret data features and relations
How it's managed	
Algorithms are detected by data analysts to examine specific variables in data sets	Algorithms are largely self-directed on data analysis once they're put into production

Figure 3.2:Differences between machine learning and deep learning.

3.3.2 Why deep learning

The development of deep learning was designed to perform automatic feature extraction from raw data without any handcraft features tool and also can be performed in huge data space, as it depicted in (figure 3.3)

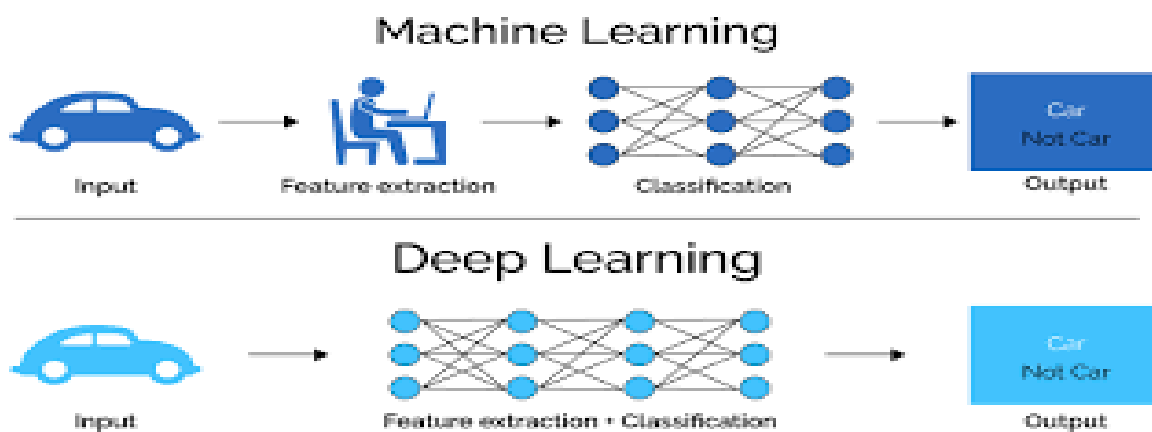


Figure3.3:The process of ML classic compared to that of Deep Learning.

Deep learning models are trained by using large amount of data and a combination of many layer sets that learn features directly from the data without the need for prior feature extraction, which took too much time-consuming step.

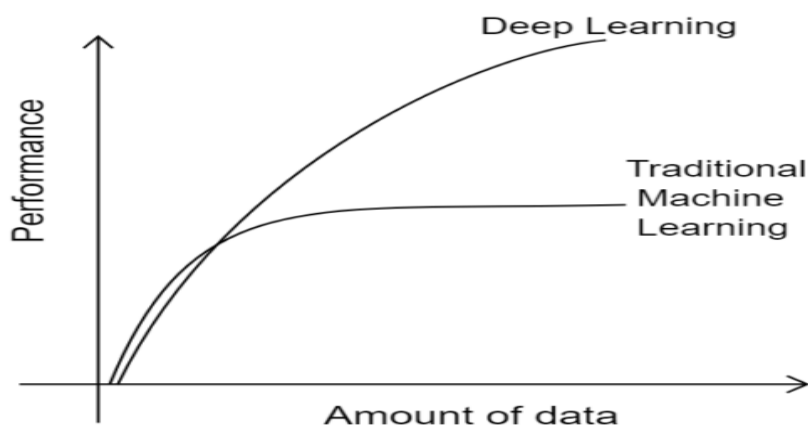


Figure 3.4:The difference in performance between DL and most ML algorithms in depending on the amount of data.

The main differences between DL and traditional ML is its performance as the scale of data increases when the data provided increases (figure 3.4), deep learning algorithms become more convenient, this is because DL algorithms need a large amount of data. contrary to many conventional ML algorithms, which can receive a specific amount of data, sometimes called “Performance Tray”.

3.3.3Different architectures of Deep Learning

There are a wide variety of buildings and algorithms used for deep learning .Over the past 20 years there have been five deep learning structures: recurrent neural networks (RNNs), long short-term memory (LSTM)/gated recurrent unit (GRU), convolutional neural networks (CNNs), deep belief networks (DBN), and deep stacking networks (DSNs).LSTM and CNN are two of the oldest methods on this list, but also one of the most widely used in various applications.

Architecture	Application
RNN	Speech recognition, handwriting recognition
LSTM/GRU network	Natural language text compression, handwriting Recognition, speech recognition, image captioning
CNN	Image recognition, video analysis, natural language processing
DBN	Image recognition, information retrieval, natural language understanding, failure prediction
DSN	Information retrieval, continuous speech recognition

Table 3.1: Different architectures of Deep Learning.

3.3.4 Deep Learning Frameworks



Figure 3.5: Different DL frameworks.

3.3.5 Convolutional Neural Network

The secret success of CNN is to well have simulated the brain cell mechanism to abstract the data based on its information, for example, an image can be classified based on pixel values, shape geometry, edge and so on. on other hand, convolutional neural network has a different architecture than standard neural network (Multi-Layer Perceptron), thus is consisting of three layers: input layer, hidden layer and output layer, each layer is made up of a set of neurons, where each layer is fully connected to all neurons in the layer before, finally there is a last fully connected layer (the output layer) that represent the prediction. CNNs consist of multiple layers of small neuron collections that process portions of the input image, called receptive field. The main applications of convolutional neural networks are related with image recognition such as image classification, object detection, facial recognition. However, CNNs application aren't limited to computer vision but also has been adopted in universal fields like biological analysis, electric vehicle, smart grid, robotic, mechanic (fault detection). Costuming an CNN network for any task, it consists a set of one or more of each of the following layers: convolution layer, ReLU (rectified linear units) layer, pooling layer,

fully connected layer and loss function (during the training process). The following figure illustrates the CNN network for character recognition.

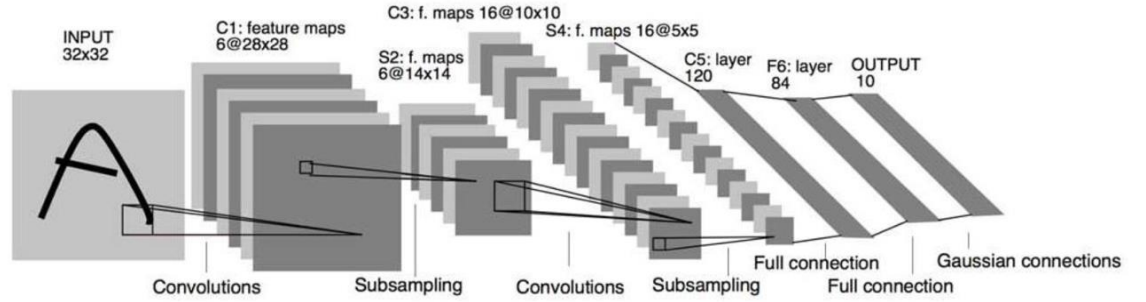


Figure 3.6: Illustration of CNN network.

Proposed approach

The MIMO antenna produces a better spectral efficiency, that it implies having a perfect CSI knowledge. However, its computation is not trivial due to the highly dynamic nature of mm-Wave channel [25]. To leverage the channel estimation under high constraints, we suggest the deep learning performance as a good candidate to estimate the optimal beamformer vector. Obviously, the DL has already shown his capability to solving a complex problem in different eras. In fact, deep learning approaches have proven their success in several successful applications of DL in wireless communications problems such as channel estimation [26], [27], analog beam selection [28], [29], and also hybrid beamforming [28], [30]–[32]. In particular, DL-based techniques have been shown [26], [31], [32], [34], [35] to be computationally efficient constructin grelevant beamformers and leverage to imperfect channel inputs when compared with the conventional methods. In [24], they adopted the machine learning method (Support vector machine) to select the relevant beamforming vectors. in [36], the authors employed deep auto-encoders to construct an efficient beamformer vectors trained from the sparse matrix of channel. Motivated by these results and inspired from [37], we employed the CNN network-based beamforming enabled to compute the specter efficiency from both the precoder and combiner respectively. So, we employ convolutional neural networks (CNNs) with specifics layers. The CNN network is trained through data within 3 dimensions, is referred to the channel matrix with three components. This data is generated from different channel realizations with synthetic noise added to each input data. Then, the following layers after being fine-tuned are dedicated to construct the output layer. Thus, is relies on the optimum solution of the problem (eq), in which the CNN network gives better performance within less computation time. our proposed deep neural network consists of two separate CNNs (Figure 3.7) to estimate the beamformers vector from the precoder and combiner.

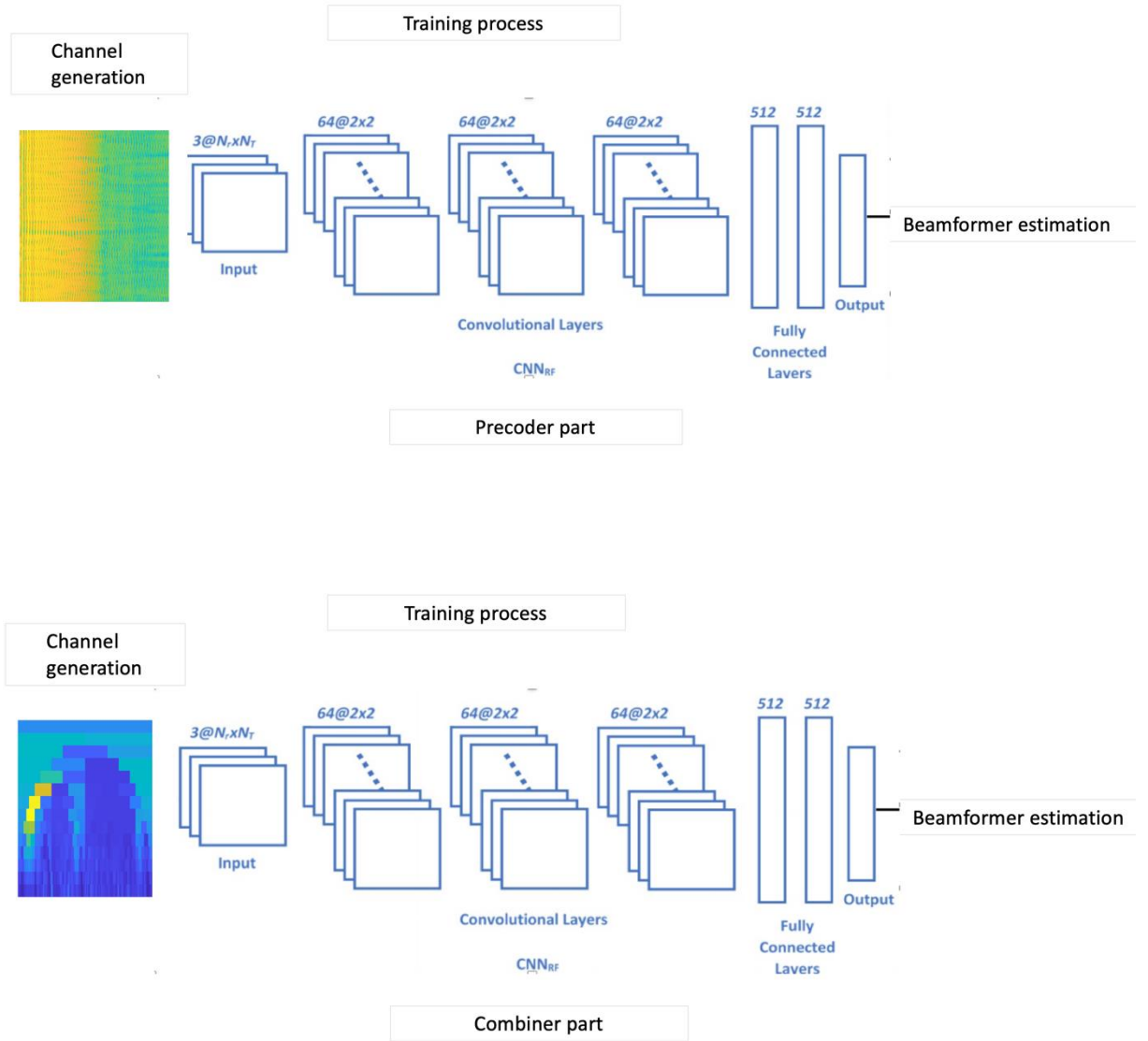


Figure 3.7: The proposed Deep learning approach for precoder and combiner task.

1-The steps of the deep learning approach in MIMO hybrid design is summarized in Algorithm :

3.3.6 Algorithm OF CNN

Input: $L, N, N_T, N_R, N_R, N_T^{RF}, N_R^{RF}, SNR_{TRAIN}$

Output: Training data D_F and D_W

- 1: Generate $\{\mathbf{H}^{(n)}\}_{n=1}^N$ with $\{F_{RF}^{(n)}\}_{n=1}^N$ and $\{W_{RF}^{(n)}\}_{n=1}^N$
 - 2: for $1 \leq n \leq N$ and $1 \leq l \leq L$ do
 - 3: $[\mathbf{H}^{(l,n)}]_{i,j} \sim \text{CN}([\mathbf{H}^{(l)}]_{i,j}, \sigma_{TRAIN}^2)$
 - 4: Find by solving (chap.2 eq.2.16) for $F_{RF}^{(qF,l,n)}, 1 \leq qF \leq Q_F$
 - 5: Construct $\dot{F}_{RF}^{(l,n)}$ and $F_{BB}^{(l,n)}$ from $F_{RF}^{(qF,l,n)}$
 - 6: Find qW by solving (chap.2 eq.2.17) for $W_{RF}^{(qW,l,n)}, 1 \leq qW \leq Q_W$
 - 7: Construct $\hat{W}_{RF}^{(l,n)}$ and $W_{BB}^{(l,n)}$ from $W_{RF}^{(qW,l,n)}$
 - 8: $[[X^{(l,n)}]::,1]_{i,j} = |[H^{(l,n)}]_{i,j}|$
 - 9: $[[X^{(l,n)}]::,2]_{i,j} = \text{Re}\{[H^{(l,n)}]_{i,j}\}$
 - 10: $[[X^{(l,n)}]::,3]_{i,j} = \text{Im}\{[H^{(l,n)}]_{i,j}\} \forall i,j$
 - 11: $z_F^{(l,n)} = \text{vec}\{\dot{F}_{RF}^{(l,n)}\}, z_W^{(l,n)} = \text{vec}\{\hat{W}_{RF}^{(l,n)}\}$
 - 12: end for n,l
 - 13: Training data for CNN_F and CNN_W is obtained as
- $$D_F = ((X^{(1,1)}, z_F^{(1,1)}), \dots, (X^{(L,N)}, z_F^{(L,N)})).$$
- $$D_W = ((X^{(1,1)}, z_W^{(1,1)}), \dots, (X^{(L,N)}, z_W^{(L,N)})).$$

Where:

- H : Channel matrix .
- CNN_F : CNN of precoder.
- CNN_W : CNN of combiner.
- F_{RF}, W_{RF} : denote the feasible sets of analog beamforming.

In data generation, N different realizations of channel matrices $\mathbf{H}^{(n)}$ for different user locations are generated together with the corresponding sets $F_{RF}^{(n)}$ and $F_{RF}^{(n)}$. Then for each realization, L noisy channel matrices are obtained where the added element-wise synthetic noise is defined by $\text{SNR}_{\text{TRAIN}} = 20\log(\frac{|[H]_{l,j}|^2}{\sigma_{\text{TRAIN}}^2})$. To account for the changes in the wireless environment, we use three different $\text{SNR}_{\text{TRAIN}}$ levels.

In our work, we have compared the robustness of the deep learning approach against two algorithms, called Spatially Sparse Precoding via Orthogonal Matching Pursuit and Manifold Optimization Based Hybrid Precoding for the Fully-connected Structure.

3.3.7 Algorithms of Improve Spectral Efficiency

3.3.7.1 OMP Algorithm (Algorithm1 Spatially Sparse Precoding via Orthogonal Matching Pursuit)

Is one such iterative algorithm that finds the sub-optimal solution:

- Resolves big problem to small optimization problems.
- In each iteration one non zero location of the sparse solution is found and the residual gets updated.
- Uses k iterations to find k non zero locations of the sparse signal.

Require: $\mathbf{F}_{opt}$

1: $\mathbf{F}_{RF}$ = Empty Matrix

2: $\mathbf{F}_{res} = \mathbf{F}_{opt}$

3: **for** $i \leq N_t^{RF}$ **do**

4: $\Psi = \mathbf{A}^* \mathbf{F}_{res}$

5: $k = \underset{\ell=1, \dots, N_{cl}N_{ray}}{\text{argmax}} (\Psi \Psi^*)_{\ell, \ell}$

6: $\mathbf{F}_{RF} = [\mathbf{F}_{RF} \mid \mathbf{A}_t^{(k)}]$

7: $\mathbf{F}_{BB} = (\mathbf{F}_{RF}^* \mathbf{F}_{RF})^{-1} \mathbf{F}_{RF}^* \mathbf{F}_{opt}$

8: $\mathbf{F}_{res} = \frac{\mathbf{F}_{opt} - \mathbf{F}_{RF} \mathbf{F}_{BB}}{\|\mathbf{F}_{opt} - \mathbf{F}_{RF} \mathbf{F}_{BB}\|_F}$

9: **endfor**

10: $\mathbf{F}_{BB} = \sqrt{N_s} \frac{\mathbf{F}_{BB}}{\|\mathbf{F}_{RF} \mathbf{F}_{BB}\|_F}$

11: **return** $\mathbf{F}_{RF}, \mathbf{F}_{BB}$

OMP is:

- an iterative algorithm : it fin x element-by-element in a step-by-step iterative manner.

- a greedy algorithm: at each stage, the problem is solved optimally.

The OMP starts the search by finding a column of A with maximum correlation with measurements y at the first step and there after at each iteration it searches for the column of A with maximum correlation with the current residual.

Where:

- F_{RF} : The analog precoding matrix.
- F_{BB} : The analog beamforming matrix.
- $k = \underset{\ell=1, \dots, N_{cl}N_{ray}}{\operatorname{argmax}} (\Psi\Psi^*)_{\ell,\ell}$: Find the array response vector which the optimal precoder maximum projection.
- $F_{RF} = [F_{RF} \mid A_t^{(k)}]$: Appends the selected array response vector to the F_{RF} .
- $F_{BB} = (F_{RF}^* F_{RF})^{-1} F_{RF}^* F_{opt}$: Least squares solution to F_{BB} .
- $F_{res} = \frac{F_{opt} - F_{RF} F_{BB}}{\|F_{opt} - F_{RF} F_{BB}\|_F}$: Calculate “residual precoding matrix”.

3.3.7.2 Algorithm 2 Spatially Sparse MMSE Combining via Orthogonal Matching Pursuit

Require: $\mathbf{W}_{MMSE}$

1: $\mathbf{W}_{RF} = \text{Empty Matrix}$

2: $\mathbf{W}_{res} = \mathbf{W}_{MMSE}$

3: **for** $i \leq N_r^{RF}$ **do**

4: $\Psi = \mathbf{A}_r^* \mathbb{E}[yy^*] \mathbf{W}_{res}$

5: $k = \underset{\ell=1, \dots, N_{cl}N_{ray}}{\operatorname{argmax}} (\Psi\Psi^*)_{\ell,\ell}$

6: $\mathbf{W}_{RF} = [\mathbf{W}_{RF} \mid \mathbf{A}_r^{(k)}]$

7: $\mathbf{W}_{BB} = (\mathbf{W}_{RF}^* \mathbb{E}[yy^*] \mathbf{W}_{RF})^{-1} \mathbf{W}_{RF}^* \mathbb{E}[yy^*] \mathbf{W}_{MMSE}$

8: $\mathbf{W}_{res} = \frac{\mathbf{W}_{MMSE} - \mathbf{W}_{RF} \mathbf{W}_{BB}}{\|\mathbf{W}_{MMSE} - \mathbf{W}_{RF} \mathbf{W}_{BB}\|_F}$

9: **end for**

10: **return** $\mathbf{W}_{RF}, \mathbf{W}_{BB}$

Where:

- $\mathbf{W}_{RF}$: The analog combiner matrix.

3.3.7.3 MO-Alt Min Algorithm : Manifold Optimization Based Hybrid Precoding for the Fully-connected Structure

This algorithm does not need any pre-determined candidate set for the analog precoder, and it is the first attempt to directly solve the hybrid precoder design problem under the unit modulus constraints.

Input: $\mathbf{F}_{\text{opt}}$

1: Construct $\mathbf{F}_{\text{RF}}^{(0)}$ with random phases and set $k = 0$;

2: **repeat**

3: Fix $\mathbf{F}_{\text{RF}}^{(k)}$, and $\mathbf{F}_{\text{BB}}^{(k)} = \mathbf{F}_{\text{RF}}^{(k)\dagger} \mathbf{F}_{\text{opt}}$;

4: Optimize $\mathbf{F}_{\text{RF}}^{(k+1)}$ using Algorithm 1 when $\mathbf{F}_{\text{BB}}^{(k)}$ is fixed;

5: $k \leftarrow k+1$;

6: **until** a stopping criterion triggers;

7: For the digital precoder at the transmit end, normalize

$$\dot{\mathbf{F}}_{\text{BB}} = \frac{\sqrt{N_s}}{\|\mathbf{F}_{\text{RF}} \mathbf{F}_{\text{BB}}\|_F} \mathbf{F}_{\text{BB}}$$

Where :

Optimize $\mathbf{F}_{\text{RF}}^{(k+1)}$ using Algorithm 1 when $\mathbf{F}_{\text{BB}}^{(k)}$ is fixed $\rightarrow$ Manifold optimization for analog precoder.

- N_T : Number of transmitting antennas.
- N_s : Number of data stream.

In each iteration of the MO-Alt Min algorithm, a conjugate gradient descent search is needed to update the analog precoder. In particular, when updating the analog precoder in each iteration, we need to search on the complex circle manifold repeatedly to find a local

optimum with zero gradient of the cost function. The complexity of the MO-Alt Min algorithm is relatively high. the update of the analog precoder involves a line search algorithm, i.e., Algorithm1, so the nested loops in the MO-Alt Min algorithm will slow down the whole solving procedure.

Furthermore, will result in two matrices of dimension $N_{RF}^t N_T \times N_s N_T$ which scales with the antenna size and results in an exponential increase of the computational complexity in the MO-Alt Min algorithm. Despite the high complexity, we note that the MO-Alt Min algorithm based on manifold optimization directly solves the hybrid precoder design problem under unit modulus constraints, which will improve the spectral efficiency when compared to existing algorithms. Therefore, this algorithm can serve as a benchmark of the performance in terms of spectral efficiency.

3.4 Numerical Simulations and Results

In this section, we evaluate the performance of our proposed approach. The performance of CNN based hybrid precoder in term of spectral efficiency is compared against state of the art SDR alt-min and SIC algorithms. To do, we have made three experiences:1) the effect of the number antennas selection,2) the effect of number of layers 3) the effect of function straining (SGDM, ADAMA, ROPMS). These experiences are performed by using MATLAB (R2021a) as a simulation environment: Pentium processor pc Intel Core I05 GPU with frequency 2.4 GHz, RAM: 8Go Windows 10(64 bits).

Our proposed deep neural network depicted in figure 3.8 is applied for the precoding and combining design. To predict the best value of F_{BB} , F_{RF} , W_{BB} and W_{RF} from the CNN network with different setting of fine-tuning parameters, by the training function algorithm is applied. For our framework, the training methodology CNN-based hybrid beamforming precoder and combiner design can be divided into three steps for:

3.4.1 MIMO channel generation

Firstly, we have generated the channel matrix that is computed through the best channel as to reduce the matrix dimension to avoid the singular values. To train our system, the channel matrix is assigned with corresponding target label for antenna selection and hybrid precoding.

Let the input data H channel matrix be a $N_R \times N_T \times 3$ with $c = 3$ channels. Thus, is complex matrix which is divided into three components: real, imaginary and absolute values, respectively.

To be in a realistic model, we have made different generation set of N channels. For each realisation, element wise operation made between the noisy channel and synthetic noise. As result, we have a new matrix with size of $N_R \times N_T \times 3 \times NL$.

3.4.2 Hybrid beamforming estimation using CNN network (precoder and combiner)

Each CNN is composed of L layers (Convolution layer, Max Pooling, ReLu layer, Dropout, Fully connected layer, and regression layer). The channel matrix assumed the first layer with size of $8 \times 8 \times 3$. Then, we costumed our network with 3 convolutional layers with 16 filters of size 2×2 . In order to reduce the parameters computation consumed and over fitting phenomena while the CNN is trained, we have applied dropout function (with 50% probability). Two fully connected layer with 64 nodes being added before applying the output regression layer with size of $N_T \times N_T^{RF}$ for precoding and $N_R \times N_R^{RF}$ for combining design. The RELU activation function is also added after each convolution layer. The output layer for both CNN based precoder and combiner, is recovered with the size of $Output^{N_T \times N_T^{RF}}$ $Output^{N_R \times N_R^{RF}}$, respectively. The training process of both CNNs is identical but with different configuration parameters. After having our network created, we applied find tuning step to train our network and to predict the best values for the precoder F_{BB}, F_{RF} and combiner: W_{BB}, W_{RF} .

3.4.3 Spectral efficiency computation

Here, the spectral efficiency of the CNN based hybrid beamforming estimation is computed by using (eq2.9 in chap 2):

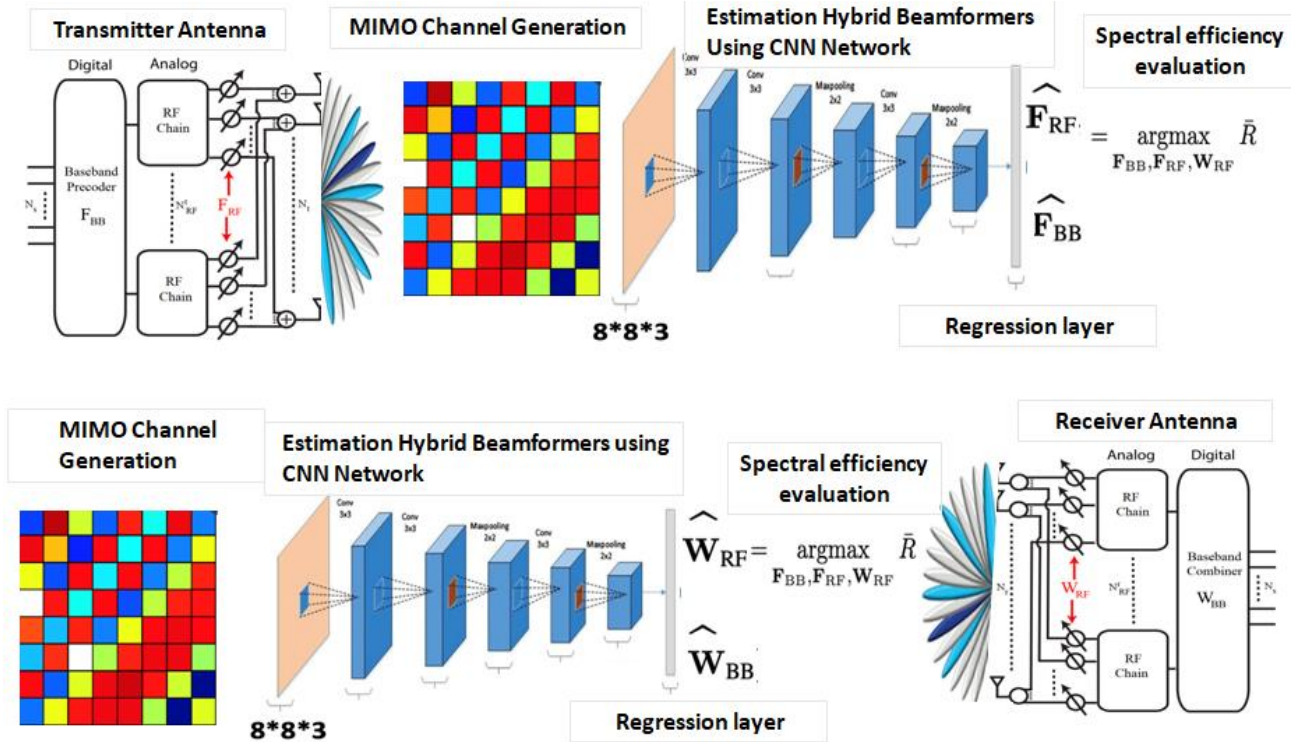


Figure 3.8: The proposed network architecture used both for Precoder (Top) and Combiner design.

3.4.3.1 The First Experience

In the first experience, we evaluate the performance of the three algorithms, by setting of antenna number (transmission and receiver). Uniform planner array with $N_T = 36$ or 64 and $N_R = 16$ for the transmitter and receiver respectively, are generated. For RF chain selection, the $N_T^{RF} = N_R^{RF}$ is kept as 4.

For CNNs, the training data is generated for $N = L = 100$ realizations. SGD algorithm is used for network parameters with learning rate of 0.009 and mini-batch size 5000 with 1000 epochs. For each channel matrix trial, the propagation environment is modeled with $N_c = 4$ and $N_{ray} = 5$ for each clusters with angle spread of 5° for all transmit and receive azimuth and elevation angles which are uniform randomly selected from the interval $[-60^\circ, 60^\circ]$ and $[-20^\circ, 20^\circ]$ respectively.

The RMSE function is used as the training function. During the training phase, cross validation is made randomly to split the full generating data to training and test data.

Figure (a) shows the performance for three algorithms with spectral efficiency estimation. The CNN based hybrid precoder is outperforming the PE alt-min and SOMP algorithms. In other words, we can say that the CNN is successfully selected the best analog beamformers which maximize the spectral efficiency.

In Figure (b) and Figure(c), Transmitter and receiver antennas are varied and the spectral efficiency is plotted along the SNR interval. It shows the performance enhancement by the CNN algorithm over the compared algorithms. CNN has a SE almost 10 bps/Hz more than the Analog beamforming with $N_t = N_r = 16$.

One of the reasons for the enhancement spectral efficiency is that it is possible to form narrower beams by RF chain arrays with larger number of antennas at the Transmitter and receiver antennas. It significantly contributes towards improving the total achievable SE, which is especially appealing for mm-Wave massive MIMO systems.

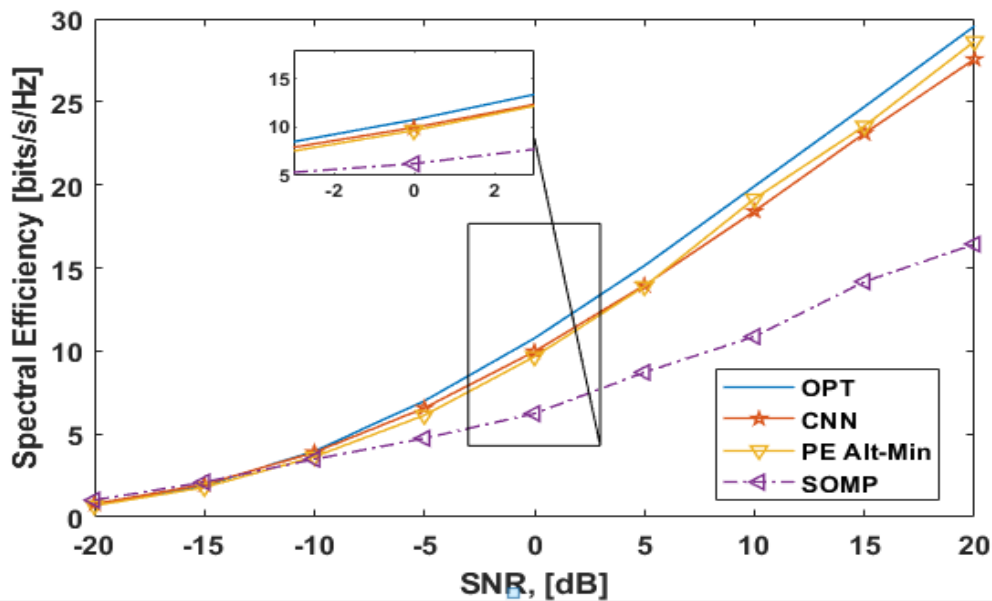


Figure (a) Spectral efficiency $N_T = 16, N_R = 4, N_S = 3$.

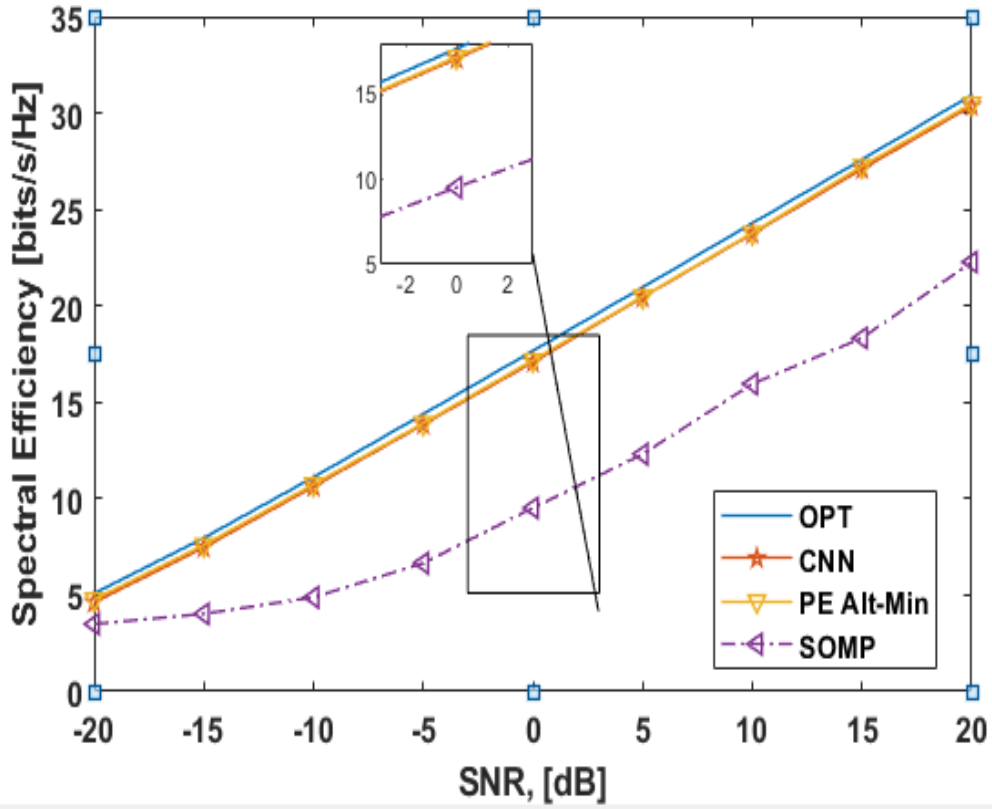


Figure (b) Spectral efficiency $N_t = 64, N_r = 16, N_T^{\text{RF}} = N_T^{\text{RF}} = 4, N_s = 2$.

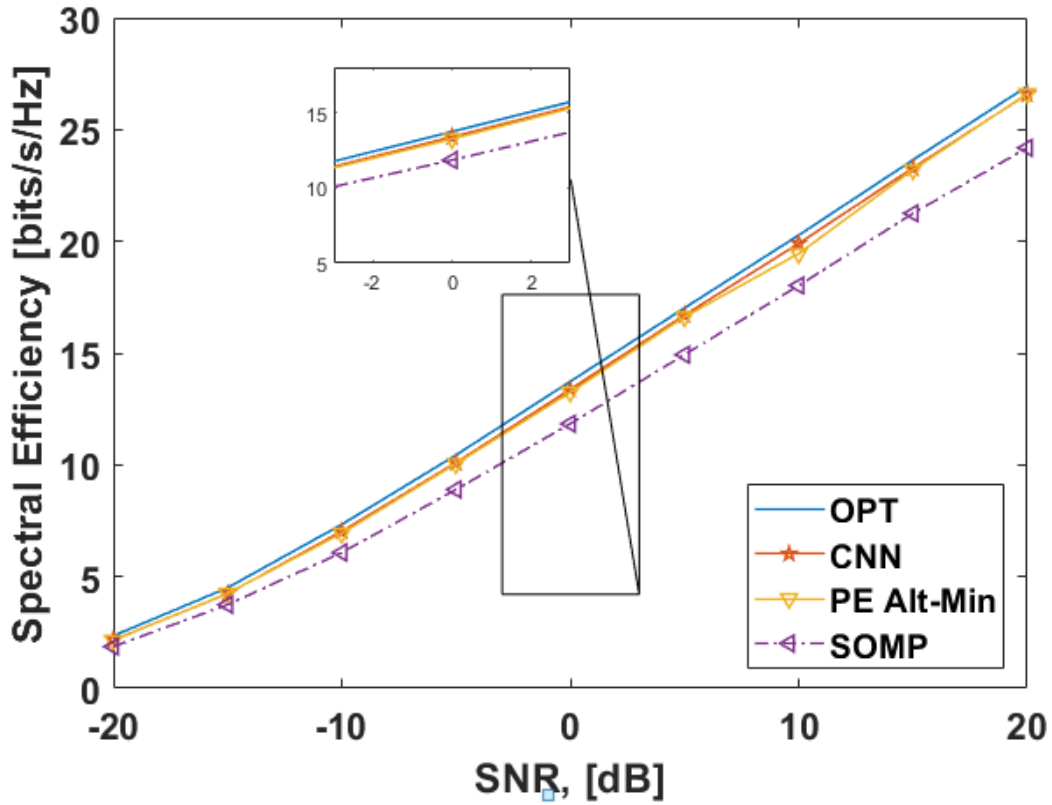


Figure (c) Spectral efficiency $N_t = 16, N_r = 16, N_T^{\text{RF}} = N_T^{\text{RF}} = 4, N_s = 2$.

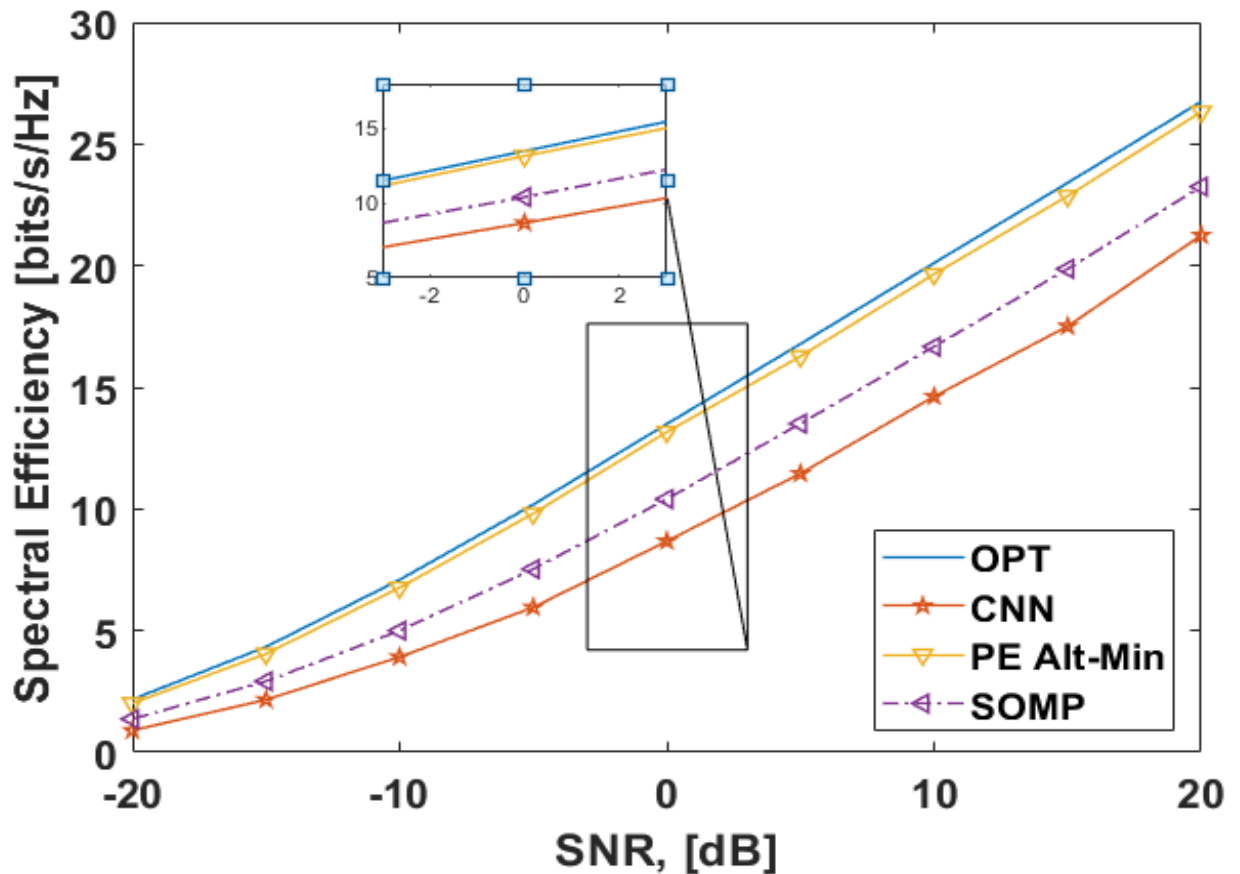
3.4.3.2 The second Experience

In the second experience, we studied the effect CNN network parameters selection on the spectral efficiency estimation. It worth that the hyper parameter CNN tuning increases the training time consummation that implies further energy resources on the MIMO resources allocation. In addition, each layer handled at least one arithmetic operation, and consequently leads to increase the execution time and CNN parameters resources.

In Fig (a),(b),(c) we present the achievable sum-rate performance of the algorithms with respect to different SNR levels. We have fixed antenna number. The figure shows the layer graph that is yielded from our CNN network.

From figure, we can see clearly that the effectiveness of CNN-MIMO is diminued due to the number of layers used in this experience, and the PE alt-min and SOMP algorithms achieved a highest result. And we notify that the performance of CNN-MIMO was also decreased with the kernel of 4*4. (See figure):

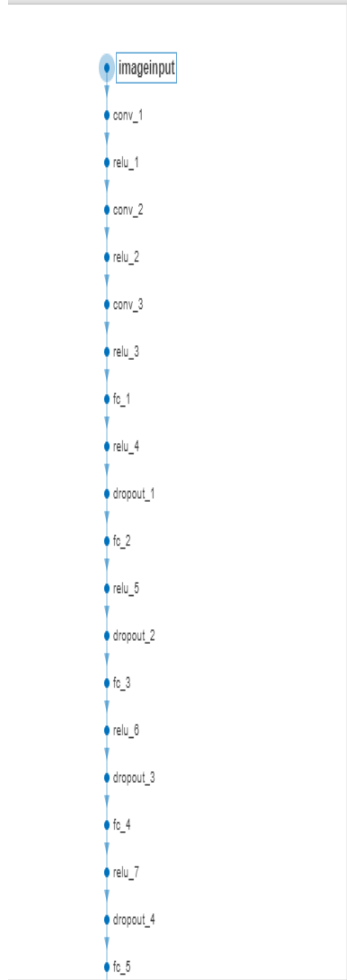
In case of the parameters: $N_S=2$, $N_T = 16$, $N_R=16$, $N_T^{RF} = N_T^{RF} = 4$.



Figure(a) Spectral efficiency for 7 layers and Kernel size=2*2.

Layer type	Activation Unit	Dropout	Kernel Size
Conv1	ReLU	-	2*2
Conv2	ReLU	-	2*2
Conv3	ReLU	-	2*2
Fc1	ReLU	√	2*2
Fc2	ReLU	√	2*2
Fc3	-	√	2*2
Fc4	-	√	2*2
Fully Connected			
Output	Regression		

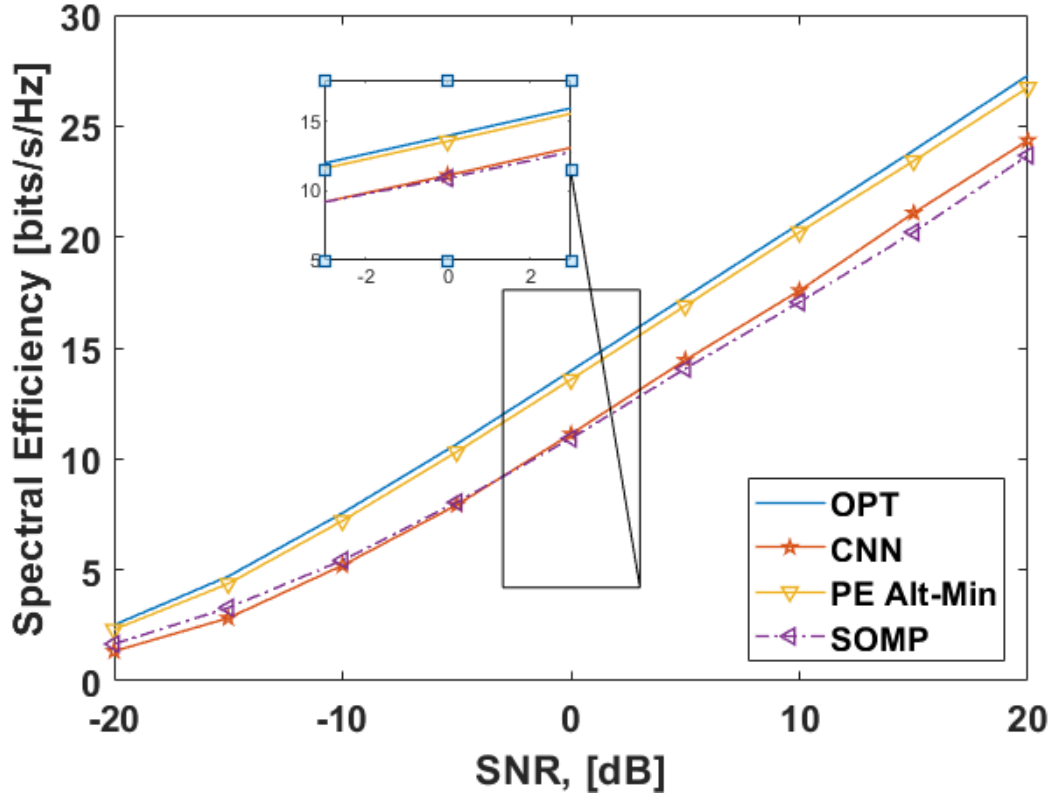
Table 3.2: CNN Layers architectures.



ANALYSIS RESULT				
	Name	Type	Activations	Learnables
3	relu_1 ReLU	ReLU	15×15×8	-
4	conv_2 8 2×2×8 convolutions with stride [1 1] and padding [0 0 0 0]	Convolution	14×14×8	Weights 2×2×8×8 Bias 1×1×8
5	relu_2 ReLU	ReLU	14×14×8	-
6	conv_3 64 2×2×8 convolutions with stride [1 1] and padding [0 0 0 0]	Convolution	13×13×64	Weights 2×2×8×64 Bias 1×1×64
7	relu_3 ReLU	ReLU	13×13×64	-
8	fc_1 1024 fully connected layer	Fully Connected	1×1×1024	Weights 1024×10816 Bias 1024×1
9	relu_4 ReLU	ReLU	1×1×1024	-
10	dropout_1 50% dropout	Dropout	1×1×1024	-
11	fc_2 256 fully connected layer	Fully Connected	1×1×256	Weights 256×1024 Bias 256×1
12	relu_5 ReLU	ReLU	1×1×256	-
13	dropout_2 50% dropout	Dropout	1×1×256	-
14	fc_3 256 fully connected layer	Fully Connected	1×1×256	Weights 256×256 Bias 256×1
15	relu_6 ReLU	ReLU	1×1×256	-
16	dropout_3 50% dropout	Dropout	1×1×256	-
17	fc_4 128 fully connected layer	Fully Connected	1×1×128	Weights 128×256 Bias 128×1
18	relu_7 ReLU	ReLU	1×1×128	-
19	dropout_4 50% dropout	Dropout	1×1×128	-

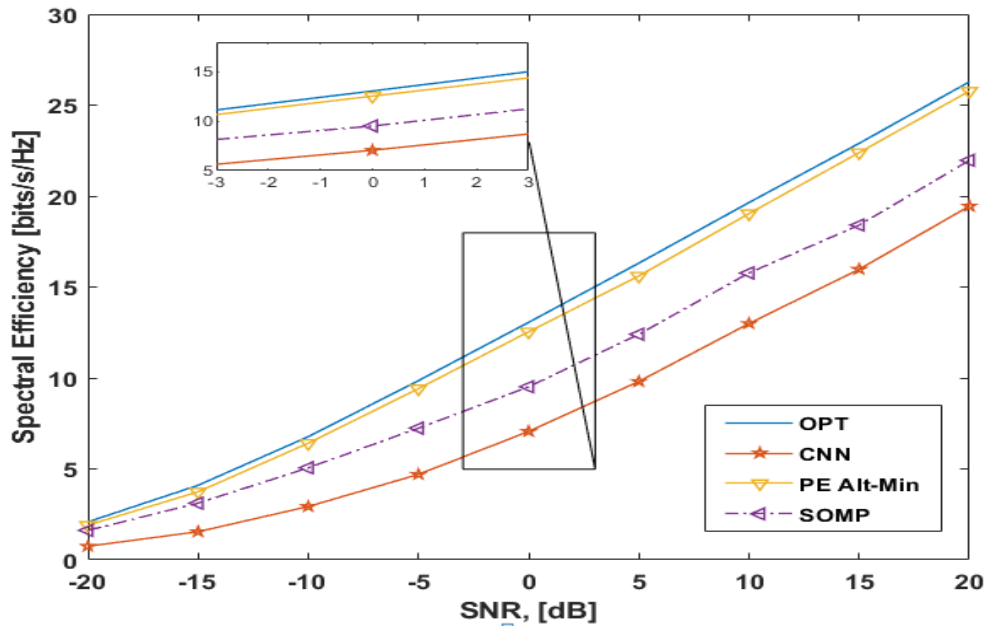
Figure 3.10: Convnet F_{RF} Selection.

In case of the parameters: $N_S=2$, $N_T = 16$, $N_R=16$, $N_T^{RF} = N_T^{RF} = 4$.



(b) Spectral efficiency for 11 layers and Kernel size=4*4.

In case of the parameters: $N_S=2$, $N_T = 16$, $N_R=16$, $N_T^{RF} = N_T^{RF} = 4$.



(c) Spectral efficiency for 11 layers for Kernel size=3*3.

3.4.3.3 The third Experience

The effect of training Function (SGDM,ADAMA,ROPMS)

In the last experience, the performance is evaluated for varying type of training functions and its parameters, namely (SGDM, ADAMA, ROPMS). where the layers are set of 4. Table summaries up the different parameters involved in SGDM function. The figure shows the training progress through SGDM function. Notably, our network with SGDM performs better than the other training functions. We also see that the performance our network closely when using SGDM and ADAMA algorithms (Fig,..). However, this gap appears due to the insufficient exhaustive research experiences. Hence, it is suggested to develop more effective algorithms of training functions that give us a good performance. In fact, for investigating the convergence of the CNN performance through different training functions, the Error rate versus no. of iterations is plotted in Figure. It is observed that the convergence of the SGMD algorithm is faster than the existing algorithms and has a major implementation benefit for the realistic scenarios.

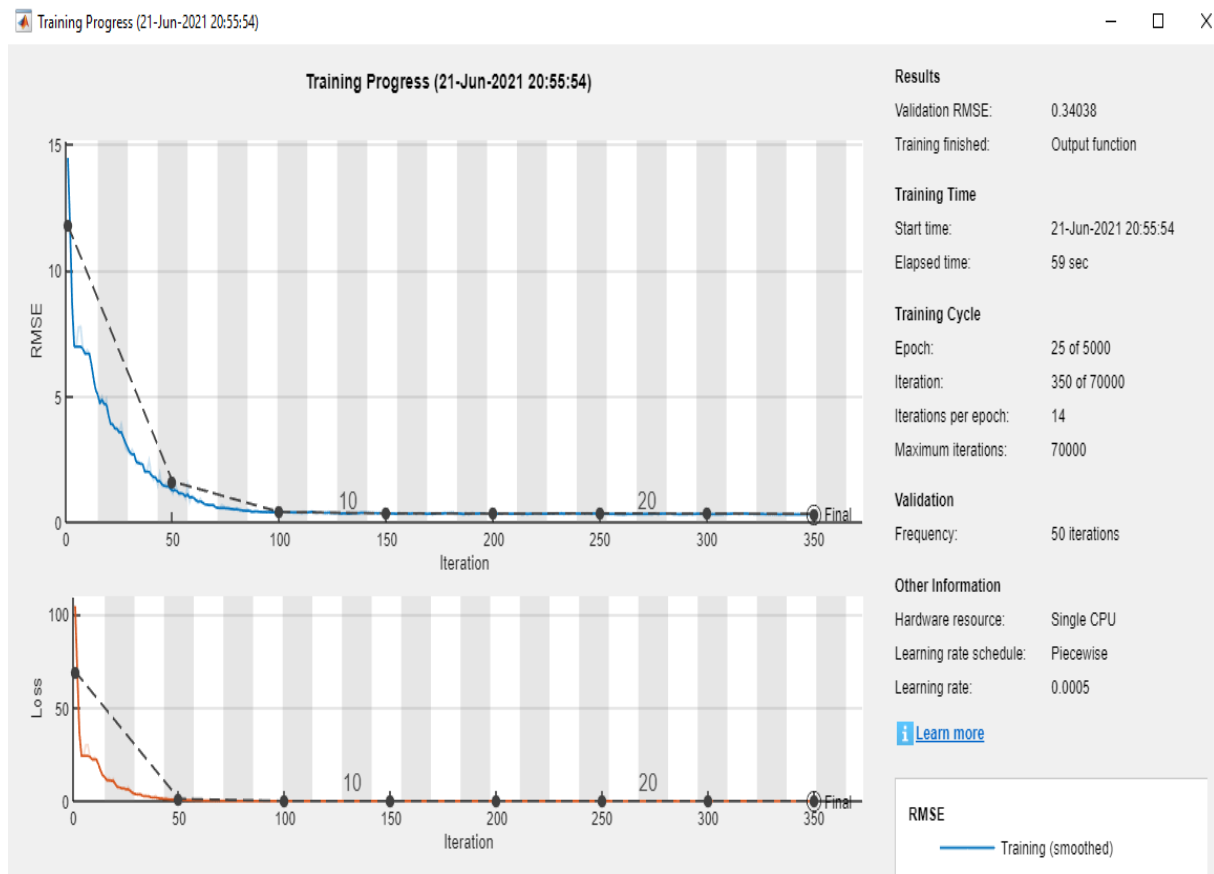
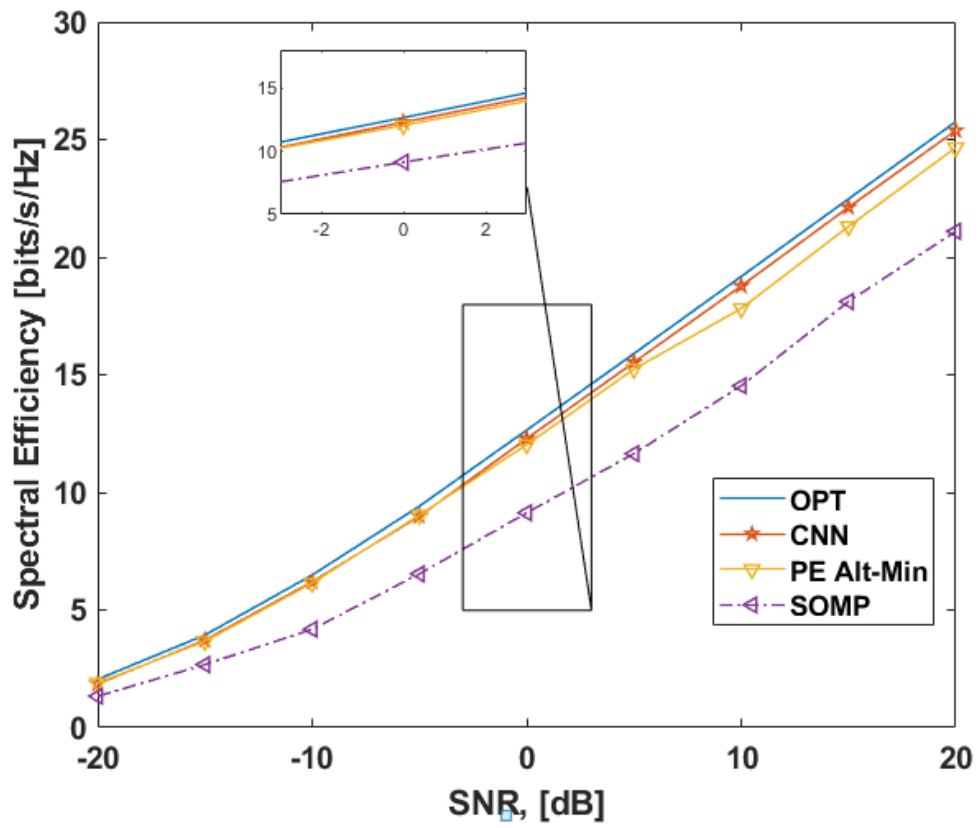
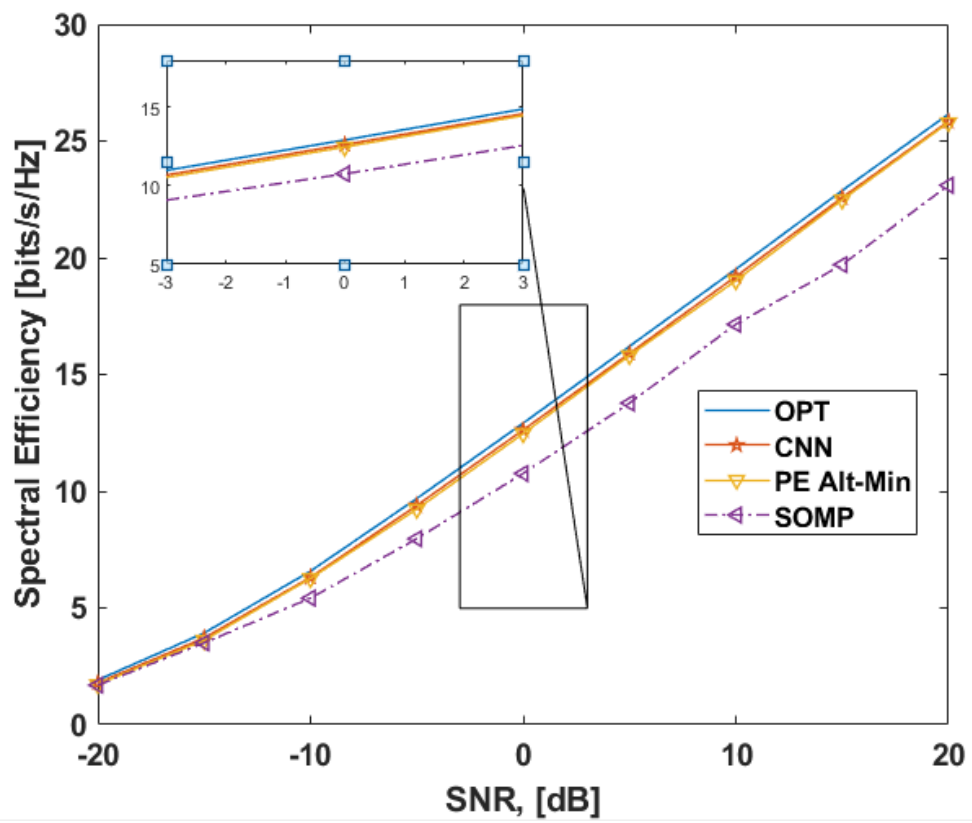


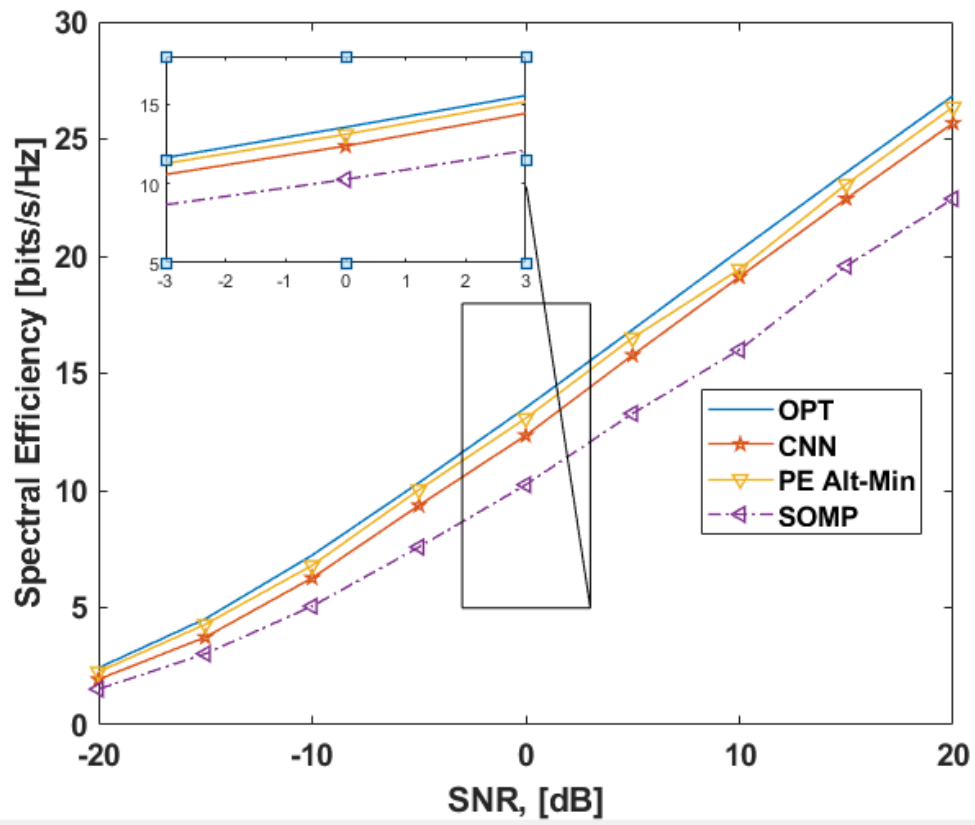
Figure 3.11: The training Progress.



(a) Spectral efficiency using function SGDM.



(b) Spectral efficiency using function ADAM.



(c) Spectral efficiency using function ROPMS.

Training function	Sgdm	Adam	Ropms
Momentum	0.9	-	-
InitialLearnRate	0.01	-	-
MaxEpochs	5000	-	-
MiniBatchSize	miniBatchSize	miniBatchSize	miniBatchSize
LearnRateSchedule	Piecewise		
LearnRateDropFactor	0.9	-	-
LearnRateDropPeriod	30	-	-
L2Regularization	0.0001	-	-
ExecutionEnvironment	Auto	-	-
ValidationFrequency	validationFrequency	validationFrequency	validationFrequency
ValidationPatience	200	200	200
Plots	None	None	none
OutputFcn	info,3	info,3	info,3
GradientDecayFactor	-	0.9000	0.9000
SquaredGradientDecayFactor	-	0.9900	0.9900
Epsilon	-	1.0000e-08	1.0000e-08
InitialLearnRate		3.0000e-04	3.0000e-04
L2Regularization	0.0001	1.0000e-04	1.0000e-04
GradientThresholdMethod		l2norm	l2norm
MaxEpochs	5000	5000	5000
ExecutionEnvironment	Auto	Auto	auto
ValidationData	valDataAntennaSelection, valLabelsAntennaSelection	valDataAntennaSelection, valLabelsAntennaSelection	valDataWRFChainSelection, valLabelsWRFChainSelection
Shuffle	every-epoch	every-epoch	every-epoch

Table 3.3: Différent Parameter of Training function.

3.5 Conclusion

The hybrid beamforming design in mm-Wave MIMO systems are examined in this dissertation by incorporating deep learning-based algorithm. A series of deep learning algorithms started adopting in the wireless network field, the CNN algorithm is adopted in this study. We first provided a detailed CNN-based hybrid precoding and combiner design. Analytical results were presented to verify the effect CNN architecture and fine-tuning variations on the overall spectral efficiency estimation, delivering that the CNN can leverage the beamformer selection because of its great recognition and mapping abilities.

General Conclusion

General Conclusion

1- Concluding Remarks

Firstly, this dissertation offered a general overview of millimeter-wave massive MIMO system, showing its outcome to achieve high spectral efficiency and overall network 5G capacity. A different MIMO technology were also talked, including antenna description and beamforming types (digital, analogue and hybrid). In addition, the thesis discussed the most common antenna selection algorithms for massive MIMO. Meanwhile, we provided a comprehensive literature survey to identify the important works that tackled the hybrid beamforming design. Especially, the use of deep learning algorithm in the MIMO technology was addressed in this study. Furthermore, two conventional hybrid precoder and combiner algorithms were studied, namely SDR alt-min and SIC algorithms. Finally, simulation results indicated that the proposed algorithms achieve high spectral efficiency close to those aforementioned algorithms. We have studied the CNN performance related to its common parameters (number of layers, kernel size, epoch, training function and so on). They have an approximately linear mapping with the percentage of selected antennas, which is desired but unexpected due to the nonlinear nature of the fine-tuning parameters selections.

2-Future Research Directions

The current study can be improved by incorporating other deep learning algorithms such as long short-term memory, generative, graph deep models. Another promising direction is to apply deep learning in the antenna selection issue to alleviate the issues related to large antenna arrays and resources allocation. To reduce the channel feedback information which implies using small data, we will incorporate the transfer learning can be suitable in this case.

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Abstract

Abstract

MIMO antenna has offered a promising potential to speed up the 5G evolution. However, the number of antenna arrays and resource allocations lead to decreasing the spectral efficiency or the capacity of 5G networks. To deal with these issues, the hybrid precoder and combiner design has been proposed to alleviate the computation complexity related to the number of fully digital beamformers selected. This dissertation examines the design of the hybrid precoder and combiner (HPC) in mm-Waves by integrating a deep learning algorithm. In particular, we have investigated the potentiality of the CNN algorithm on the estimation of the analog precoders and combiners parameters respectively. Results obtained from simulations demonstrate the improved performance of the CNN-MIMO algorithm in contrast to the existing algorithms and can achieve promising results.

Keys words: Hybrid precoding/combining, mm-Wave, SNR, Spectral efficiency, Deep Learning.

Résumé

L'antenne MIMO a offert un potentiel prometteur pour accélérer l'évolution de la 5G. Cependant, le nombre de réseaux d'antennes et les allocations de ressources conduisent à diminuer l'efficacité spectrale ou la capacité des réseaux 5G. Pour résoudre ces problèmes, la conception hybride du précodeur et du combineur a été proposée pour alléger la complexité de calcul liée au nombre de formateurs de faisceaux entièrement numériques sélectionnés. Cette thèse examine la conception du précodeur et combineur hybride (HPC) en mm-Waves en intégrant un algorithme d'apprentissage en profondeur. En particulier, nous avons étudié la potentialité de l'algorithme CNN sur l'estimation des paramètres des précodeurs et combineurs analogiques respectivement. Les résultats obtenus à partir des simulations démontrent l'amélioration des performances de l'algorithme CNN-MIMO par rapport aux algorithmes existants et peuvent obtenir des résultats prometteurs.

Mots clés: Précodage/combinaison hybride, mm-Wave, SNR ; Efficacité spectrale, Deep Learning

المخلص

قدم هوائي MIMO إمكانية واحدة لتسريع تطور 5G ومع ذلك ، فإن عدد صفائف الهوائي وتخصيصات الموارد يؤدي إلى تقليل الكفاءة الطيفية أو قدرة شبكات الجيل الخامس. للتعامل مع هذه القضايا ، تم اقتراح تصميم جهاز التشفير المسبق والمجمع المختلط للتخفيف من تعقيد الحساب المرتبط بعدد محولات الحزم الرقمية المختارة بالكامل. تبحث هذه الرسالة في تصميم جهاز الترميز المسبق والمجمع (HPC) في موجات ملم من خلال دمج خوارزمية التعلم العميق. على وجه الخصوص ، لقد بحثنا في إمكانية خوارزمية CNN على تقدير المعلمات التناظرية والمجمعات على التوالي. تظهر النتائج التي تم الحصول عليها من عمليات المحاكاة الأداء المحسن لخوارزمية CNN-MIMO على عكس الخوارزميات الحالية ويمكن أن تحقق نتائج واحدة.

الكلمات الرئيسية : الترميز المسبق / الدمج الهجين ، الموجة مم ، SNR ؛ الكفاءة الطيفية ، التعلم العميق