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- Ghenabzia Mohammed Bachir
- Bekkouche Ikram

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Evaluation of massive MIMO performance in Terms of Spectral Efficiency

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❖ **Chairman**	Hatiri Masoud
❖ **Examiner**	Tidjani Amina
❖ **Supervisor**	Ajgou Riadh
❖ **Co-Supervisor**	Guettal Lemya

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بسم الله الرحمن الرحيم

١٤٣٨

Thanks

Praise be to Allah, Lord of the worlds. We thank Almighty God for granting us the strength, patience, and success in completing this work.

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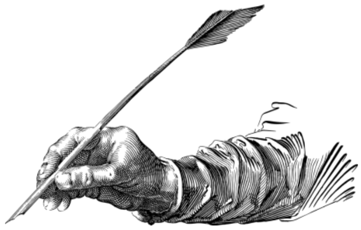
Dedications

بسم الله الرحمن الرحيم

(قل اعملوا فسيرى الله عملكم ورسوله والمومنين)

إله لا يطيب اليل إلا بشكره ولا يطيب النهار إلا بطاعته ولا تطيب اللحظات إلا بذكره الله جل وجلاله
" إلى من بلغ الرسالة وأدى الأمانة "سيدنا محمد صلى الله عليه وسلم
انتهت الرحلة ، لم تكن قصيرة ولم تكن سهلة ولم يكن الحلم قريبا ومهما طالت فستمضي بحلوها ومرها وفي اللحظة أكثر فخرا اهدي عملي هذا إلى كافح لأجلي إلى المصباح الذي أنار دربي ولمن احمل اسمه بكل افتخار طاب بك العمر يا سيد الرجال وطبت لي عمرا ...... والدي العزيز
إلى ملاكي في الحياة ومعنى الحب وقرة عيني إلى بسمة الحياة وسر الوجود إلى من كان دعائها سر نجاحي إلى غاليتي وجنة قلبي .... أمي الغالية
إلى ضلعي الثابت الذي لا يميل إلى من رزقت بهم سندا وملاذي الأول والأخير إلى من أزالوا من طريقي أشواك الفشل إخوتي وأخواتي
. إلى استاذي الدكتور أجقو رياض الذي قدم لنا يد العون وكان سندا بعد الله لنكمل هذه المذكرة
والحمد لله على حسن التمام والختام

إكرام بكوش



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Dedications

To all those who gave their all and taught me that success only comes with patience and perseverance. To the light that illuminated my path, and to the lamp that never goes out in my heart... To the one who gave the most precious thing he had, and from whom I drew my strength and self-respect... To... my father

To the one who created paradise beneath his feet and stayed awake all night for my comfort and prayers, to the great human being in whose eyes I always wished to see joy on a day like this... to... my mother

To my strong rib and support throughout my days, to the one who strengthened my arm and was my support and eyes... my sisters

To all those who helped and supported me on this path, to my friends and my graduation companion.

I dedicate to you this success and the fruit of my success that I have always desired. Today, by the grace of Almighty God, I graduated from Wadi University.

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....

Abstract

This master thesis investigates the spectral efficiency performance of communication systems employing Massive MIMO (Multiple-Input Multiple-Output) technology—one of the cornerstone solutions for fifth-generation (5G) networks and a key enabler for future sixth-generation (6G) networks. The primary objective is to analyze the influence of critical system parameters, including the number of base station antennas, channel conditions, precoding techniques, and pilot contamination, on spectral efficiency. To enhance system performance, the roles of advanced signal processing techniques such as beamforming, Zero-Forcing (ZF), Maximum Ratio Transmission (MRT), and Minimum Mean Square Error (MMSE) precoding are explored, alongside the integration of Intelligent Reflecting Surfaces (IRS). Simulation results, based on Rician fading models in MATLAB, demonstrate that increasing the number of antennas significantly boosts spectral efficiency, especially when appropriate precoding methods are employed. However, beyond a certain antenna threshold, performance gains diminish due to residual interference and pilot contamination effects. The findings confirm that while Massive MIMO can substantially increase network capacity and reliability, achieving optimal performance depends on careful resource allocation, interference mitigation, and the use of scalable, low-complexity techniques.

Key word: Massive MIMO, SE, precoding, pilot contamination.

Résumé

Ce mémoire étudie l'efficacité spectrale des systèmes de communication utilisant la technologie Massive MIMO (Multiple-Input Multiple-Output), l'une des solutions phares des réseaux de cinquième génération (5G) et un catalyseur essentiel pour les futurs réseaux de sixième génération (6G). L'objectif principal est d'analyser l'influence de paramètres système critiques, notamment le nombre d'antennes de station de base, les conditions de canal, les techniques de précodage et la contamination du pilote, sur l'efficacité spectrale. Pour améliorer les performances du système, le rôle des techniques avancées de traitement du signal, telles que la formation de faisceaux, le forçage à zéro (ZF), la transmission à rapport maximal (MRT) et le précodage à erreur quadratique moyenne minimale (MMSE), est exploré, ainsi que l'intégration de surfaces réfléchissantes intelligentes (IRS). Les résultats de simulation, basés sur des modèles d'évanouissement Riciens dans MATLAB, démontrent qu'une augmentation du nombre d'antennes améliore significativement l'efficacité spectrale, notamment lorsque des méthodes de précodage appropriées sont utilisées. Cependant, au-delà d'un certain seuil d'antenne, les gains de performance diminuent en raison des interférences résiduelles et des effets de la contamination du pilote. Les résultats confirment que même si le

MIMO massif peut augmenter considérablement la capacité et la fiabilité du réseau, l’obtention de performances optimales dépend d’une allocation rigoureuse des ressources, de l’atténuation des interférences et de l’utilisation de techniques évolutives et peu complexes.

Mots clés : Massive MIMO, SE, precoding, pilot contamination.

الملخص

تبحث رسالة الماجستير هذه في أداء الكفاءة الطيفية لأنظمة الاتصالات التي تستخدم تقنية MIMO (MIMO المتعدد المدخلات والمخرجات المتعددة) الضخمة – وهي أحد الحلول الأساسية لشبكات الجيل الخامس (G٥) وعامل تمكين رئيسي لشبكات الجيل السادس المستقبلية. ويتمثل الهدف الأساسي في تحليل تأثير معلمات النظام الحرجة، بما في ذلك عدد هوائيات المحطة القاعدية، وظروف القناة، وتقنيات الترميز المسبق، والتلوث التجريبي، على الكفاءة الطيفية. ولتعزيز أداء النظام، يتم استكشاف أدوار تقنيات معالجة الإشارات المتقدمة مثل تشكيل الحزم، والإجبار الصفري (ZF)، والإرسال بأقصى نسبة (MRT)، والترميز المسبق لأدنى متوسط خطأ مربع (MMSE)، إلى جانب دمج الأسطح العاكسة الذكية (IRS). تُظهر نتائج المحاكاة، استنادًا إلى نماذج التلاشي الريسيان في برنامج MATLAB، أن زيادة عدد الهوائيات يعزز الكفاءة الطيفية بشكل كبير، خاصة عند استخدام طرق الترميز المسبق المناسبة. ومع ذلك، بعد عتبة هوائي معينة، تتضاءل مكاسب الأداء بسبب التداخل المتبقي وتأثيرات التلوث التجريبي. تؤكد النتائج أنه على الرغم من أن تقنية MIMO الضخمة MIMO يمكن أن تزيد من سعة الشبكة وموثوقيتها بشكل كبير، فإن تحقيق الأداء الأمثل يعتمد على التخصيص الدقيق للموارد وتخفيف التداخل واستخدام تقنيات قابلة للتطوير ومنخفضة التعقيد.

الكلمة الرئيسية: MIMO الهائل ، الكفاءة الطيفية، الرميز المسبق ، التلوث التجريبي

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abbreviations List

MIMO: Multiple-Input Multiple-Output

5G : Fifth-generation

IRS : Intelligent Reflecting Surfaces

6G : Sixth-generation

ZF : Zero-Forcing

MRT : Maximum Ratio Transmission

MMSE : Minimum Mean Square Error

SE : Spectral Efficiency

SISO : Single Input Single Output

SIMO : Entrée unique Sortie multiple

MISO : Sortie unique à entrées multiples

SNR : Signal-to-noise ratio

MU-MIMO : Multi-User MIMO

BS : Base Station

UTs : User Terminals

TDD : Time Division Duplex

FDD : Frequency Division Duplex

SU-MIMO : Single-User MIMO

CDMA : Code Division Multiple Access

MIMO-OFDM : Multiple Input Multiple Output - Orthogonal Frequency Division Multiplexing

CSI : Channel State Information

UL: Uplink

DL : Downlink

UE : User Equipment

DPP : Dirty Paper Precoding

TH : Tomlinson Harashima precoding

VP : Vector Perturbation

R-ZF : Regularized ZF

WF : Water Filling

IUI : Inter-User Interference

SINR : Signal to Interference plus Noise Ratio

MRC : Maximal Ratio Combining

LS : Least Squares

ICA : Independent Component Analysis

SVD : Singular Value Decomposition

EVD : Eigen value Decomposition

RF : Radio Frequency

DOA : Direction of Arrival

ADCs : Analog to Digital Converters

DACs : Digital to Analog Converters

General Introduction

General Introduction

Massive MIMO (Massive Multiple-Input Multiple-Output) is widely recognized as one of the core technologies that underpin the capabilities of fifth-generation (5G) wireless communication systems. Its primary strength lies in its ability to dramatically enhance spectral efficiency, energy efficiency, and overall network capacity, making it essential for meeting the ever-increasing demands for high data rates, ultra-reliable communication, and massive device connectivity.

The key idea behind Massive MIMO is the deployment of a very large number of antennas—typically in the order of tens or even hundreds—at the base station. This enables spatial multiplexing, allowing the system to serve multiple users simultaneously on the same time-frequency resources. As a result, the system can achieve much higher throughput compared to traditional MIMO systems.

However, the implementation of Massive MIMO is not without its challenges. One of the most prominent issues is pilot contamination, which occurs when non-orthogonal pilot sequences are reused across cells, leading to inaccurate channel estimation. In addition, the complexity of channel estimation increases with the number of antennas, especially in fast-fading or highly dynamic environments. Moreover, the computational burden associated with signal processing tasks such as precoding, detection, and decoding grows significantly as the antenna array size increases.

To tackle these challenges and unlock the full potential of Massive MIMO, several advanced techniques have been proposed and integrated into system design. These include beamforming, which focuses the transmission energy toward intended users to reduce interference; precoding, which optimizes the signal transmission based on channel conditions; and Intelligent Reflecting Surfaces (IRS), which consist of reconfigurable passive elements that can reflect signals in a controlled manner to enhance wireless propagation.

Each of these techniques contributes differently to system performance, and their effectiveness can vary significantly depending on factors such as user distribution, environmental conditions, and system configuration. Therefore, understanding their individual and combined impacts is critical for optimizing Massive MIMO systems.

This research is structured into three main chapters, each addressing a specific aspect of the study:

Chapter One introduces the fundamental concepts of Massive MIMO technology. It explains how it fits within the broader 5G ecosystem and outlines its key architectural elements. The chapter also presents the main motivations for adopting Massive MIMO, such as improved spectral and energy efficiency, and highlights the theoretical foundations upon which the technology is built.

Chapter Two investigates the main factors affecting spectral efficiency in Massive MIMO systems. It explores various precoding techniques, the impact of beamforming, the role of accurate channel estimation, the influence of the number of antennas, and the performance gains achievable through the integration of IRS. This chapter aims to build a strong understanding of the technical parameters that influence system behavior.

Chapter Three presents the simulation results obtained using MATLAB software. The simulations evaluate how different precoding methods, variations in the number of antennas, and the presence of pilot contamination affect the spectral efficiency of the system. The findings provide quantitative insights into the trade-offs and performance implications of these factors in practical scenarios.

Chapter I: Massive MIMO technique for 5G

I.1 Introduction

Massive MIMO (Multiple Input Multiple Output) is a key technology in fifth-generation (5G) wireless communication systems. It extends traditional MIMO by deploying a large number of antennas at the base station, enabling simultaneous transmission to multiple users over the same time-frequency resources. This results in significant improvements in spectral efficiency, energy efficiency, and network capacity. By exploiting spatial multiplexing and beamforming, Massive MIMO enhances data rates and reduces interference. However, its implementation poses challenges such as pilot contamination, complex channel estimation, and increased computational load. This chapter introduces the basic concepts of Massive MIMO and highlights its role in improving the performance of modern wireless networks.

I.2 Traditional MIMO and massive MIMO

MIMO (Multiple-Input Multiple-Output) is a wireless technology that enhances data transmission by utilizing multiple antennas at both the transmitter and receiver. It leverages the phenomenon of multipath propagation, where transmitted signals reflect off walls, ceilings, and other objects, arriving at the receiver from different angles and at slightly different times. By exploiting these multipath signals, MIMO introduces a spatial dimension that significantly improves both performance and coverage.

This technology enables multiple antennas to simultaneously send and receive independent spatial data streams, effectively increasing network capacity and efficiency. MIMO-equipped antennas operate intelligently by combining signals arriving via different paths at different times, thereby enhancing the receiver's signal strength. Additionally, spatial diversity techniques optimize the use of extra antennas—if the number of antennas exceeds the number of spatial streams, the surplus antennas contribute to signal diversity, improving reliability and extending coverage. [1]

I.3 Principles of MIMO

As previously explained, the main factor affecting signal propagation is the channel, which introduces various impairments such as fading, frequency shifts, and time delays due to multipath propagation. Unlike traditional communication systems, diversity-based systems leverage these propagation effects to enhance performance. MIMO systems achieve these improvements by employing the following techniques:

Spatial Diversity: Also referred to as antenna diversity, this technique uses multiple antennas to mitigate signal degradation.

Frequency Diversity: This approach involves transmitting the same signal over different frequencies. However, it requires careful consideration of the channel's coherence bandwidth and the frequency spread caused by multipath effects and transmission distances.

Temporal Diversity: By transmitting the same signal at different time intervals within the channel's coherence time, temporal diversity can be achieved. This technique is influenced by factors such as the mobility of the receiver and the carrier frequency. [2]

I.4 Types of MIMO

There are four basic antenna configuration models, including:

- ✓ SISO - Single Input Single Output.
- ✓ SIMO - Entrée unique Sortie multiple.
- ✓ MISO - Sortie unique à entrées multiples.
- ✓ MIMO - Multiple Input Multiple Output.

I.4.1 SISO (Single Input Single Output)

Like a person talking to another person using a single mouth and a single ear. The message is transmitted in a straightforward way without additional enhancements. as shown in the figure I.1

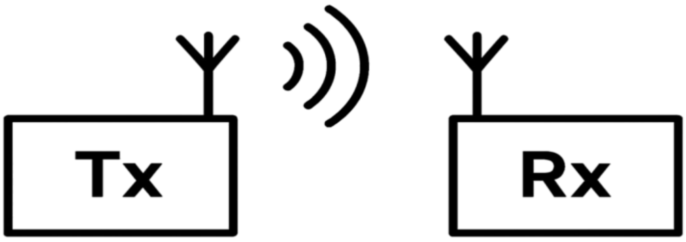

Figure I.1. SISO - Single Input Single Output

The primary advantage of a SISO system lies in its implementation simplicity. Unlike MIMO systems, it requires no complex processing related to diversity techniques (such as spatial or frequency diversity). However, its performance is limited: channel interference and fading have a more significant impact compared to a MIMO system utilizing diversity mechanisms. Additionally, its maximum capacity is constrained by Shannon's Law, where the data rate directly depends on the available bandwidth and the signal-to-noise ratio (SNR) [2].

$$C = B\ log_2(1 + SNR)\ [bit/s] \qquad \textbf{I.1}$$

C: capacity [bit/s]

B: bandwidth [Hz]

SNR: Signal to Noise Ratio [dB]

I.4.2 SIMO (Single Input Multiple Output)

The SIMO configuration (or MISO – Multiple Input Single Output) refers to a scenario where the transmitter has a single antenna, while the receiver is equipped with multiple antennas as shown in the figure I.2 , architecture, also known as diversity reception, is primarily used to mitigate channel fading effects by combining signals from independent sources. It has been employed for decades in shortwave listening/reception stations to counteract disturbances caused by ionospheric fading and interference.

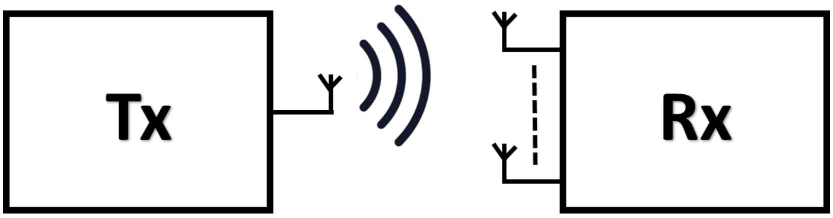

Figure I.2. SIMO (Single Input Multiple Output)

The SIMO system offers the advantage of relatively straightforward implementation, despite requiring complex signal processing at the receiver. While its use is suitable for many applications, integration into mobile devices (such as smartphones) faces practical constraints: limitations related to size, cost, and battery consumption, which restrict the receiver's processing capabilities. [2]

I.4.3 MISO (Multiple Input Single Output)

MISO is also referred to as transmit diversity. In this configuration, the same data is redundantly transmitted from both transmitting antennas as shown in the figure I.3. The receiver can then capture the optimal signal, which it uses to extract the required data.

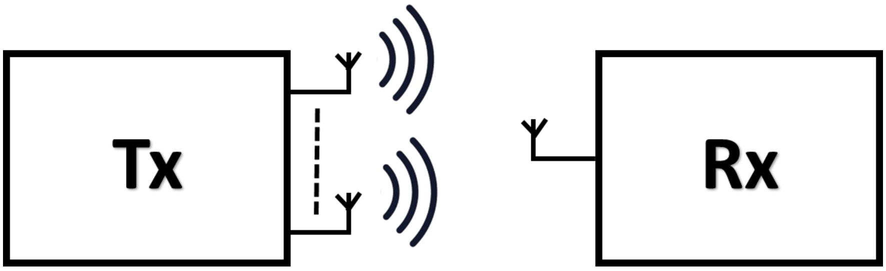

Figure I.3 MISO (Multiple Input Single Output)

The advantage of using MISO is that the multiple antennas and redundancy processing are shifted from the receiver to the transmitter. In applications such as cellular user equipment (e.g., mobile phones), this can provide significant benefits in terms of antenna space savings and reduced processing requirements at the receiver for redundancy coding. This positively impacts device size, cost, and battery lifespan, as lower processing demands result in reduced battery consumption. [2]

I.4.4 MIMO (Multiple Input Multiple Output)

MIMO (Multiple Input Multiple Output) is a wireless communication technology that utilizes multiple antennas at both the transmitter receiver. It leverages diverse signal propagation paths to transmit data (figure I.4) . Specifically, each antenna is assigned a distinct path, enabling the simultaneous use of multiple signal paths. This enhances transmission reliability and data throughput.

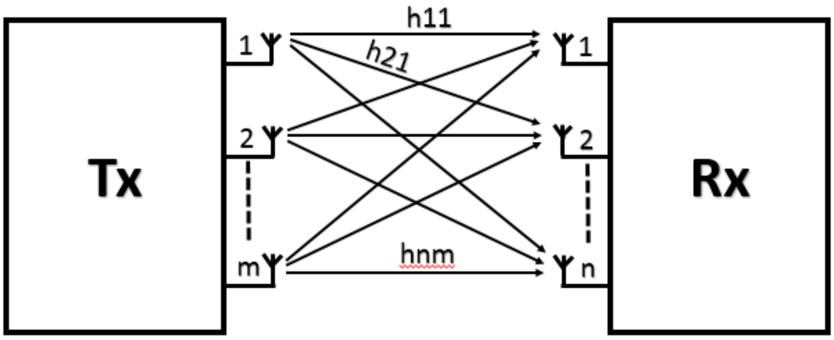

Figure I.4. MIMO (Multiple Input Multiple Output)

One of the core principles of MIMO (Multiple Input Multiple Output) systems lies in spatiotemporal signal processing, where the temporal dimension is enhanced by a spatial dimension. The latter arises from the strategic deployment of multiple antennas at distinct locations (spatial diversity). Thus, MIMO systems represent a natural evolution of smart antennas, historically used to optimize wireless network performance.

Between the transmitter and receiver, signals can travel through multiple propagation paths (multipath). Additionally, even slight movements of the antennas alter these paths. The diversity of paths depends on the number of obstacles or reflectors near or along the direct line between the two devices. Traditionally, these multipath effects were seen as sources of interference. However, with MIMO, they become an asset: they strengthen the communication link by improving the signal-to-noise ratio (SNR) or increasing the data transmission capacity. [3]

I.5 Massive MIMO

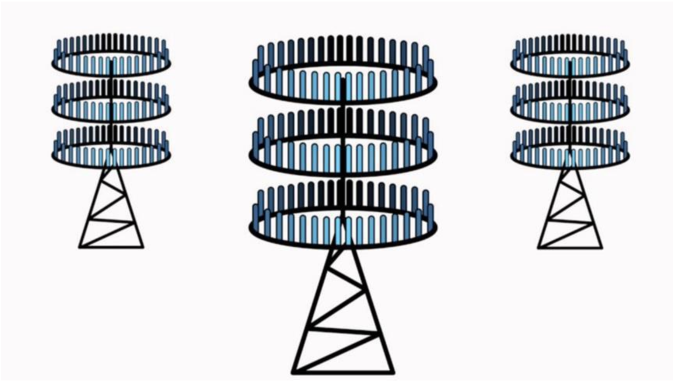

Figure I.5. An illustration of massive MIMO.

MIMO can be summarized by a key principle: spatial multiplexing in MIMO involves using the same radio frequencies to transmit different signals simultaneously. This means that multiple transmission antennas at a base station can emit different signals, and multiple receiving antennas at a device can receive and separate these signals at the same time.

Standard MIMO networks typically use two or four antennas for data transmission and the same number for reception. In contrast, Massive MIMO is a MIMO system with a significantly higher number of antennas. Massive MIMO increases the number of transmitting antennas (from dozens to over 100 elements) at a base (figure I.5) station Massive MIMO introduces two major innovations:

I.5.1 Beamforming

is a traffic signaling system for cellular base stations that identifies the most efficient data transmission path for a particular user while reducing interference for nearby users.

At massive MIMO base stations, signal processing algorithms map out the best over-the-air transmission route for each user. They can then send individual data packets in multiple directions, bouncing them off buildings and other objects in a perfectly coordinated pattern as shown in the figure I.6.

In summary, think of massive MIMO technology as a massive 3D structure that enhances both horizontal and vertical coverage capabilities.

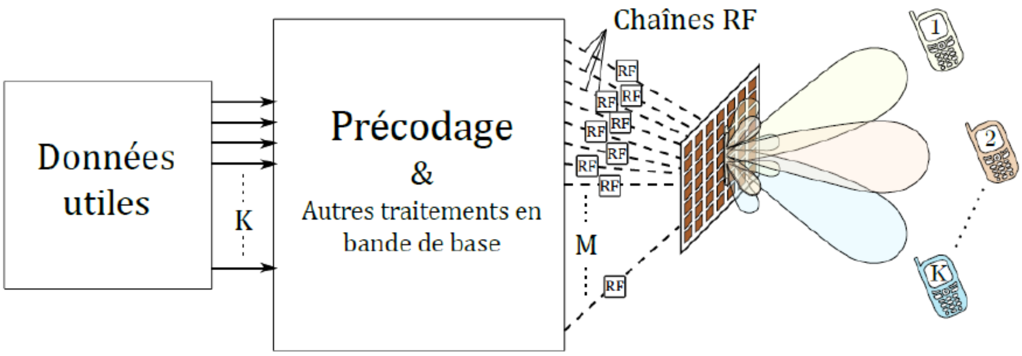

Figure I.6. Massive MIMO System in Multi-User Transmission [3].

I.5.2 MU-MIMO

further increases the total capacity per base station by enabling communication with multiple devices using the same resources, effectively creating a nearly unified edge network. The simultaneous use of multiple device antennas helps establish large-scale virtual MIMO channels. The combination of these two innovations enhances wireless transmission speeds by increasing the number of base station antennas without consuming additional bandwidth or increasing power levels. [4]

I.6 Characteristics of Massive MIMO

Massive MIMO is a type of MU-MIMO (Multi-User MIMO) structure where the number of base station (BS) antennas and user terminals (UTs) is significantly high. In Massive MIMO, thousands of BS antennas can simultaneously serve dozens or even hundreds of users while utilizing the same frequency resources. Some key aspects of Massive MIMO include:

I.6.1 Scalability

The base station learns the channels through uplink training in a TDD (Time Division Duplex) operation. The time required for channel estimation remains independent of the number of BS antennas. As a result, the BS antenna array can be expanded without increasing the overhead for channel estimation.

Moreover, signal processing at each UT is independent of the number of other UTs in the system. The demultiplexing process is performed directly at the user terminals, meaning that adding or removing UTs does not affect the operation of the remaining users.

I.6.2 Massive MIMO Prefers the TDD Scheme

In Frequency Division Duplex (FDD) mode, channel estimation depends on the number of base station (BS) antennas, M. However, in Time Division Duplex (TDD) mode, the channel estimation time remains independent of M. Since Massive MIMO involves a large number of antennas, TDD operation is preferred.

In FDD systems, the number of BS antennas and user terminals (UTs) is limited by the condition $M + K < 200$, wher as in TDD systems, the constraint becomes $2K < 200$.

As shown i, the available space for FDD is significantly smaller compared to TDD. With TDD, adding extra antennas no longer impacts the resources needed for channel estimation. illustrates the overwhelming advantage of TDD over FDD for UTs, where:

The vertical axis represents the number of BS antennas. The horizontal axis represents the number of UTs.

The light blue area shows the range of device configurations possible with TDD, while the red area, which is much smaller, represents the constraints of FDD.

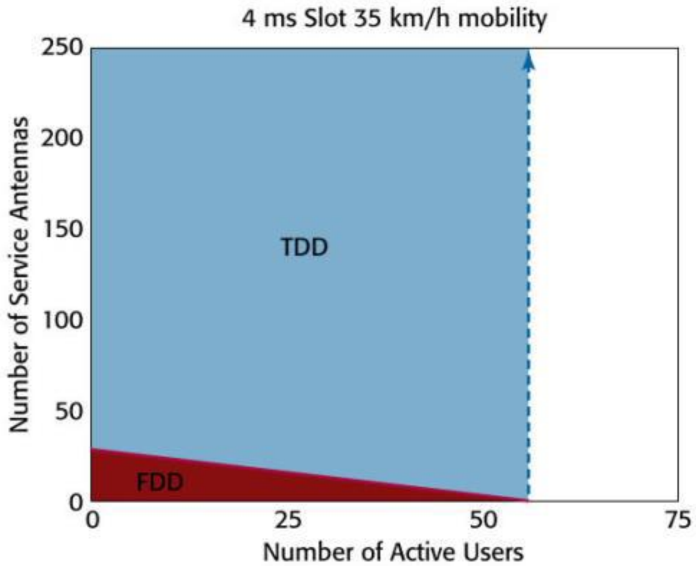

Figure I.7: Constraint of M and K on TDD and FDD for a massive MIMO system [3].

This figure I.7 highlights the overwhelming gain of TDD over FDD for user terminals (UTs). The vertical axis represents the number of base station (BS) antennas, while the horizontal axis corresponds to the number of UTs. The light blue area indicates the available device dimensions with TDD, in contrast to the much smaller red area representing FDD. [2]

I.6.3 The Antenna Array Does Not Need to Be Physically Large

For example, consider a cylindrical antenna array consisting of 128 antennas, arranged in four circles with16 dual-polarized antenna elements each. At a frequency of 2.6 GHz, the distance between adjacent antennas is approximately6 cm, which corresponds to half the wavelength. As a result, this array occupies only a physical space of 28 cm × 29 cm.

I.6.4 Massive MIMO provides favorable propagation

Favorable propagation refers to the mutual orthogonality between channel vectors at different user terminals and is one of the key advantages of radio channels in Massive MIMO. However, this aspect has not been extensively studied in detail. As the number of BS antennas increases, Massive MIMO tends to achieve more favorable propagation, which is a direct consequence of the law of large numbers. [5]

I.7 Advantages of Massive MIMO Systems

The main benefits of Massive MIMO systems can be summarized as follows: [6]

- ✓ High spectral efficiency gain
- ✓ High energy efficiency gain
- ✓ Simplified signal processing
- ✓ -Increased data rate
- ✓ Improved base station signal-to-noise ratio (SNR)
- ✓ Enhanced channel robustness.

I.8 Types of Massive MIMO

Massive MIMO (Multiple Input Multiple Output) systems can be categorized based on various criteria, including architecture, beamforming techniques, duplexing modes, frequency bands, and user focus. Here's a structured breakdown:

I.8.1 Single-User MIMO (SU-MIMO)

Due to the physical constraints of user terminals, the number of antennas on a terminal is typically much smaller than M (the number of BS antennas). As a result, SU-MIMO configurations fall into Case 1, where a large number of antennas are deployed at the base station, allowing the system to benefit from channel orthogonalization, provided that favorable propagation conditions exist.

However, SU-MIMO channels can exhibit high correlation due to the short spacing between antennas at the user terminal and the presence of a strong line-of-sight (LoS) component. From an energy efficiency perspective, using a large antenna array to serve a single user or a small number of user terminals may not be efficient as shown in figure II.8. Consequently, the implementation of Massive MIMO for SU-MIMO may be limited in practical scenarios

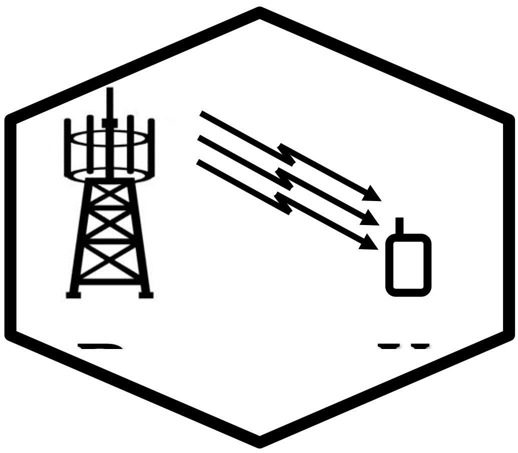

Figure I.8. Single-User MIMO (SU-MIMO)

$$y = \sqrt{PU}\ hs + w \qquad \text{I.2.}$$

Where, PU represent the SNR of the uplink, h denotes the channel response vector, s represents the symbol vector, and w the AWGN noise vector. [2]

I.8.2 Multi-User Massive MIMO

When multiple terminals are allowed to share the same time-frequency resource (see Figure I.9), MU-MIMO provides superior system efficiency compared to SU-MIMO. In this section, we consider single-cell MU-MIMO systems, where the base station serves K user terminals (UT), each terminal being equipped with one antenna. The signal received at the base station in a MU-MIMO system on the uplink is as follows:

$$y = \sum_{k=1}^{k} \sqrt{Pu}\, h_k s_k + w \qquad \text{I.3}$$

$$y = \sqrt{Pu}\, HS + w \qquad \text{I.4}$$

y : is the received signal matrix M × 1,

$h_k \in H$ Or H = $[h_1 \ldots h_k \ldots h_k]$ represents the channel vector between the BS antennas and

$s_k \in S$ Or S^T = $[S_1 \ldots S_K \ldots S_K]$ represents the symbol transmitted by the kth UT.

w represents the additive white Gaussian noise (AWGN).

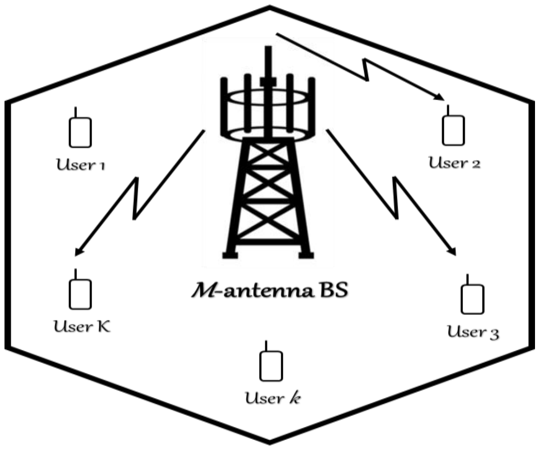

Figure I.9. Massive MU-MIMO system. An M-antenna BS serves K single-antenna UTs.

When K ≥ 2, the signal received from each user terminal interferes with those from other terminals, implying that the mutual information per terminal in MU-MIMO systems is lower than in SU-MIMO systems (even with the same transmit power per terminal). However, when M >> K, channel orthogonalization occurs, making the received signals from each terminal nearly orthogonal (i.e., interference-free) under favorable channel propagation conditions. Furthermore, since the terminals are independent, favorable channel propagation conditions are typically ensured due to the low correlation and decoupling between their antennas. This demonstrates that Massive MIMO is the optimal configuration for MU-MIMO. [2]

I.8.3 MU- Massive MIMO with Multi-Cell scenario

In this section, we analyze the constraints of non-cooperative cellular MU-MIMO (Multi-User Multiple-Input Multiple-Output) systems as the number of antennas M approaches infinity. In both single-cell and multi-cell MIMO scenarios, unbounded growth of M eliminates thermal noise and small-scale Rayleigh fading. However, in multi-cell environments, inter-cell interference caused by pilot contamination persists. The concept of pilot contamination, represents an emerging challenge in cellular MU-MIMO systems as shown in Figure I.10, though it has traditionally been associated with CDMA systems.

Channel estimation performed by the base station in cell l is disrupted by pilot signals from cell j. Consequently, the base station in cell l partially transmits its signal to terminals in neighboring cell j. Despite beamforming precoding, the interference inflicted on cell j remains asymptotically non-vanishing as $M \rightarrow \infty$.

We model a multi-user MIMO-OFDM cellular system with a hexagonal topology and NFFT subcarriers. Each cell serves K independent terminals and employs M antennas at non-cooperative base stations. The composite $M \times K$ channel matrix between the K terminals in cell l and the base station in cell j is denoted as H_{jl} . Leveraging channel reciprocity, the downlink channel matrix from base station j to terminals in cell l is expressed as H_{jl}^{T}. The received signal at the j-th base station is formulated as follows: [2]

$$\mathbf{y_j} = \sum_{l=1}^{L} \sum_{k=1}^{k} \sqrt{\mathbf{Pu}}\, \mathbf{h_{jlk} s_{lk}} + \mathbf{w} \qquad \mathbf{I.5}$$

$$\boldsymbol{y_j} = \sum_{l=1}^{L} \sqrt{\boldsymbol{Pu}}\, \boldsymbol{H_{jl} s_l} + \boldsymbol{w} \qquad \mathbf{I.6}$$

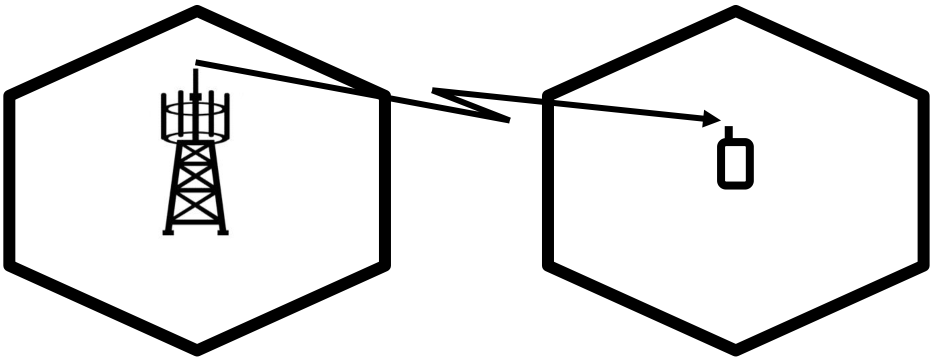

Figure I.10. The BS in the l-th cell and the k-th UT in the j-th cell**.**

I.8.4 Massive Distributed MIMO

Distributed Massive MIMO can be treated as a distinct case of MU-MIMO to further enhance system capacity by leveraging spatially dispersed antennas for transmitting and receiving signals. One of the mechanisms of distributed massive MIMO involves enabling cooperation between base stations in separate cells, which reduces inter-cell interference. However, synchronization becomes a critical challenge even for distributed antennas within the same base station.

In some cases, the massive number of antennas at the base station can be deployed at unique locations (e.g., on building rooftops). In such scenarios, synchronization remains a significant issue, and low-cost RF interfaces may also introduce additional challenges. [6]

I.9 Comparison Between Traditional MIMO and Massive MIMO

Compared to traditional MIMO, Massive MIMO offers several advantages [7]:

- ✓ Improved Spectral Efficiency (SE)
- ✓ A massive number of degrees of freedom in the spatial domain
- ✓ High system performance with simple linear precoding schemes, such as Zero-Forcing (ZF), Maximum Ratio Transmission (MRT), and Minimum Mean Square Error (MMSE)
- ✓ Simplified resource allocation.

I.10 System Model

In massive MIMO systems, a large number of antennas are deployed at the base station the system model is shown in figure I.11. The left side of the diagram represents the uplink process, while the right side corresponds to the downlink process. When users attempt to communicate with the base station, their data streams must first undergo precoding based on channel state information (CSI) acquired through the transmission of pilot sequences.

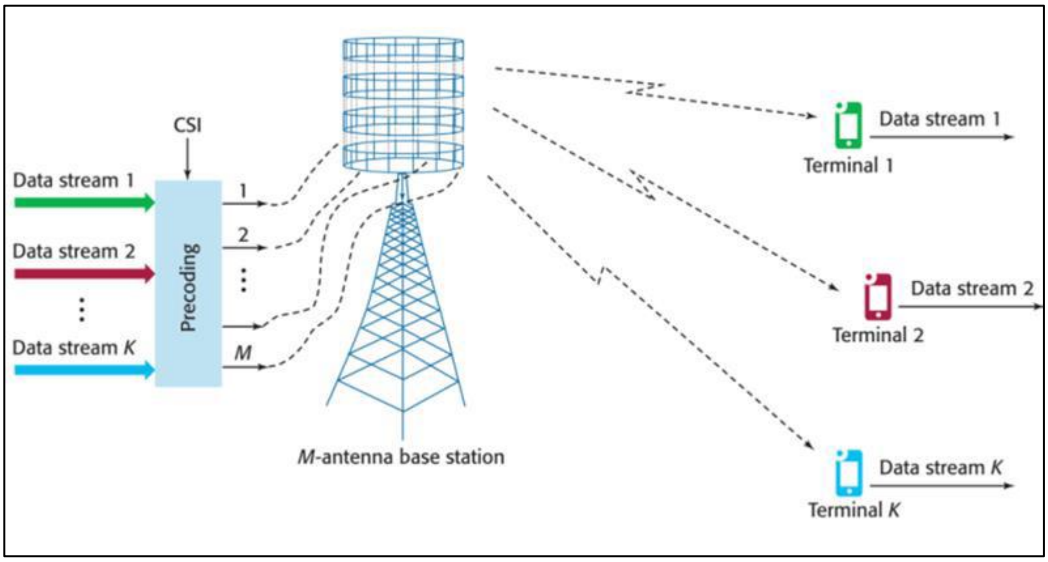

Figure. I.11. Massive MIMO System Model [7].

Based on the system model, we can easily derive a mathematical model for massive MIMO systems.

$$\bar{\boldsymbol{y}} = \boldsymbol{WHHx} + \boldsymbol{WHn} \qquad \textbf{I.7}$$

is the transmitted signal, $\bar{y}$is the received signal, $\vec{y} \in \mathbb{C}$. $W \in NT * NT$ .is the precoding matrix. The channel matrix, $H \in \mathbb{C}\ NT \times NT$. $\bar{n}$ is the noise vector.[10]

I.11 Spectral Efficiency (SE)

The efficiency of a communication system has traditionally been measured by spectral efficiency, expressed in bits/s/Hz, which is directly related to the channel capacity in bits per second. This metric indicates how efficiently the spectral resource is utilized. Spectral efficiency provides insight into the effective use of bandwidth and is defined as the ratio between the network data rate (R)and the signal bandwidth [8].

$$\mathbf{SE} = \frac{\mathbf{R}}{\mathbf{B}}\ (\mathbf{bit/s/Hz}) \quad \textbf{I.8}$$

Theorem 1: If an MMSE channel estimate is used, the ergodic uplink (UL) channel capacity of UE kin cell j is bounded by SE_{jk}^{UL}[bit/s/Hz], given by:[9]

$$\mathbf{SE}_{jk}^{UL} = \frac{\tau_u}{\tau_c}\mathrm{E}\{\log_2(1+\mathbf{SINR}_{jk}^{UL})\} \qquad [\mathbf{bit/s/Hz}] \quad \textbf{I.9}$$

Theorem 2: The ergodic downlink (DL) channel capacity of UE k in cell j is bounded by SE_{jk}^{DL} [bit/s/Hz], given by:

$$\mathbf{SE}_{jk}^{DL} = \frac{\tau_D}{\tau_c}\log_2(1+\mathbf{SINR}_{jk}^{DL}) \quad \textbf{I.10}$$

Where: $\tau_c = \tau_p + \tau_u + \tau_d$; With:

τ_c: coherence time

τ_p: UL pilot signals

τ_u: UL data signals

τ_d: DL data signals

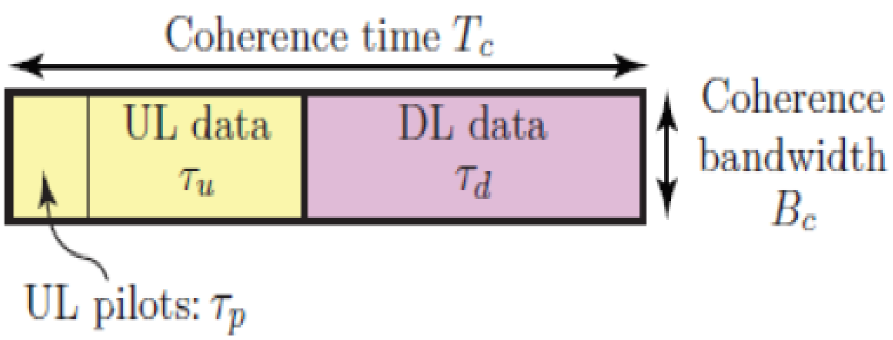

Figure I.12. Coherence Block.

I.12 Conclusion

In this section, we studied the Massive MIMO technique, which is one of the key elements contributing to the improvement of 5G networks. It is essential to meet the data requirements of applications, making it crucial in supporting 5G applications.

Chapter II: Techniques That Affect Spectral Efficiency in Massive MIMO

II.1 Introduction:

Massive MIMO systems play a crucial role in enhancing spectral efficiency in 5G and future 6G networks by deploying large antenna arrays at the base station, enabling simultaneous communication with multiple users over the same frequency band. This improvement is driven by advanced beamforming and precoding techniques that accurately focus energy toward users, reducing interference and improving signal quality. Efficient channel estimation methods are also essential to obtain reliable Channel State Information (CSI) and mitigate pilot contamination, which is a common challenge in dense deployments. To address hardware limitations and reduce system complexity, hybrid analog-digital architectures are used in combination with low-complexity algorithms. Additionally, power control and system calibration contribute to maintaining robust link quality and ensuring high data throughput, making Massive MIMO a foundational technology for next-generation wireless communication systems.

II.2 Techniques that affect spectral efficiency

Here are several key techniques that affect spectral efficiency in wireless communication systems:

II .2.1 Precoding techniques

Precoding is a concept of beamforming which supports the multi-stream transmission in multi-antenna systems. Precoding plays an imperative role in massive MIMO systems as it can mitigate the effect created by path loss and interference, and maximizes the throughput. In massive MIMO systems, the base station estimates the CSI (channel state information) with the help of uplink pilot signals or feedback sent by the user terminal. The received CSI at the base station is not uncontrollable and not perfect due to several environmental factors on the wireless channel [10]. Although the base station does not receive perfect CSI, still the downlink performance of the base station largely depends upon the estimated CSI. Thus, the base station uses the estimated CSI and the precoding technique to reduce the interference and achieve gains in spectral efficiency. The performance of downlink massive MIMO depends upon the accurate estimation of CSI and the precoding technique employed. Although the precoding technique provides immense benefits to massive MIMO systems, it also increases the computational complexity of the overall system by adding extra computations. The computational complexity increases along with the number of antennas. Thus, low complex and efficient precoders are more practical to use for massive MIMO systems. Figure II.1with M-antenna base station and N-users.

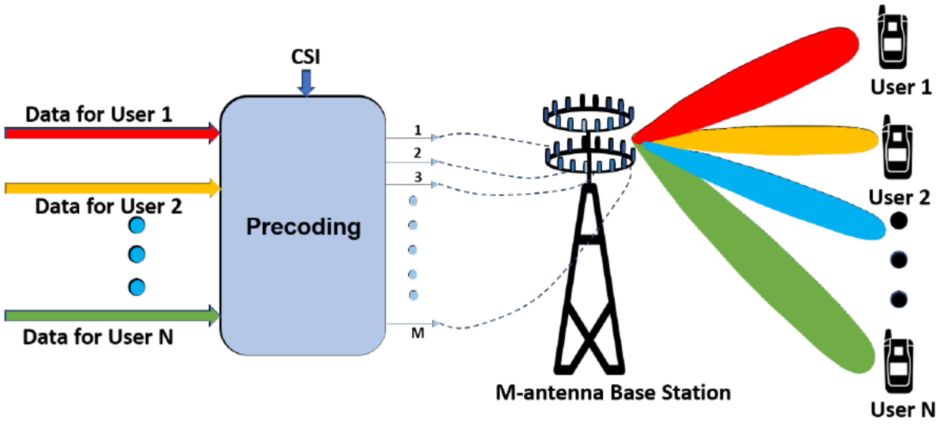

Figure II. 1. Precoding in a massive MIMO system with M antennas at base station communicating with N users. [11]

Many linear and non-linear precoders have been proposed for massive MIMO systems. Although the non-linear precoders like Dirty Paper Precoding (DPP)[12], Tomlinson Harashima precoding (TH) [13], and Vector Perturbation (VP)[14] provide better performance, these methods have very high computational complexity when we have large antenna system. The linear precoders such as Maximal Ratio Combining (MRC)[15], Zero-Forcing (ZF) [16] , Regularized ZF (R-ZF) [17] ,Water Filling (WF), and MMSE [18] have lower computational complexity and can achievenear-optimal performance.[19]

II .2.1.1 Types of precoding Techniques

Precoding is a vital technique in multi-antenna wireless systems to manage interference and enhance signal quality. The main types of precoding techniques include:

A. Zero-Forcing (ZF) Precoding:

Zero Forcing (ZF) is a spatial signal processing method that employs multiple transmitting antennas to eliminate multi-user interference, effectively mitigating inter-user interference. Classified as full-complex zero forcing among linear precoding techniques, it uses a precoding matrix designed to suppress interference between user streams, optimizing performance in massive MIMO systems [20] . ZF performs best in low-noise or high-power scenarios. When channels are ill-conditioned (leading to low SNR), ZF boosts precoded signal power but requires higher transmit energy to cancel interference. By directing signals toward intended users while creating nulls for others—termed "null-steering"—ZF applies the pseudo-inverse of the channel matrix as its precoding filter as shown in the figure II.2. This channel inversion approach is favored for simplicity and tolerance to estimation errors, though its complexity scales polynomially with users and antennas.

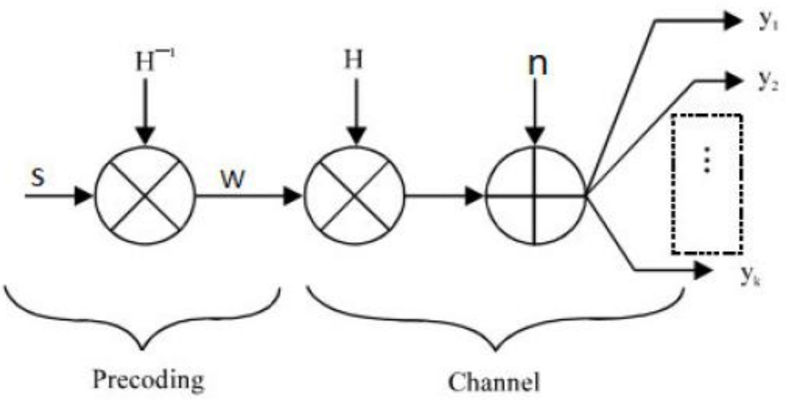

Figure . II.2. Massive MIMO system with channel inversion. [21]

In ZF precoding, the base station (BS) pre-multiplies signals with the pseudo-inverse of the channel matrix, targeting users directly. While optimal in noise-free environments, ZF amplifies additive noise, degrading performance in noisy conditions. This method cancels inter-user interference (IUI) by isolating user streams at the cost of increased power demands.

$$w_{ZF} = H^{H} (HH^{H})^{-1} \quad \textbf{II.1}$$

It's the pseudo-inverse of the channel matrix H. In the absence of additive noise, ZF precoding is an optimal precoding strategy [10]. If additive noise is present, this precoding technique amplifies the noise effect. [22]

B. Minimum Mean Square Error (MMSE) Precoding:

MMSE precoding is a linear transmit-side beamforming technique that chooses weight vectors to directly minimize the mean-square error between the transmitted and the received signals. It achieves an optimal balance between maximizing signal gain (as in MRT) and nulling interference (as in ZF) by incorporating a noise-regularization term, and hence often outperforms pure ZF or MRT in moderate SNR regimes. Closed-form MMSE precoders exist under full CSI, and numerous extensions (for example, weighted MMSE, team MMSE, symbol-level MMSE) have been proposed for applications ranging from cell-free massive MIMO to millimeter-wave systems.[22]

$$W_{MMSE} = H^{H} (HH^{H} + \alpha I)^{-1} \quad \textbf{II.2}$$

C. Maximum Ratio Transmission (MRT) Precoding:

MRT is also known as matched l ter. Its goal is to optimize the SINR at the expected target by using the conjugate transpose of the channel matrix. As a result, the MRT precoding matrix used by the BS is therefore expressed as MRT precoder is preferred because of the absence of channel matrix inversion. In addition, it is the simplest linear precoder. Since MRT computes its weight by taking the complex conjugate of a signal, it only requires a bit-ip and an adder. Given an appropriate SNR requirement, ZF prefers MRT as the number of antennas at the massive array M increases, making MRT an ideal precoder. Unlike ZF, MRT does not attempt to cancel IUI but boosts the symbol's power. When using MRT instead of ZF precoders, the polynomial complexity of ZF-based beamforming in multi-user systems with a large number of antennas is overwhelming. However, as demonstrated in, the optimality of conjugate beamforming for ZF should not be assumed in actual massive MIMO systems, as it would occur only in specic scenarios. MRT precoding, for example, outperforms only ZF when the number of concurrent users is very high, users have high mobility, or the hardware capacity at the base station is very low. Therefore, the MRT precoder is preferred because of the absence of channel matrix inversion. Since MRT computes its weight by taking the complex conjugate of a signal, it only requires a bit-ip and an adder. [22]

$$\mathbf{W_{MRT}} = \mathbf{H^{H}} \qquad \textbf{II.3}$$

D. Maximal Ratio Combining (MRC)

Maximum Ratio Combining (MRC) is a straightforward receive processing technique in which the base station (BS) maximizes the signal-to-noise ratio (SNR) of each user’s transmission stream, without considering the presence of multiuser interference. To detect the signal from the k-th user, the BS multiplies the received signal vector y by the conjugate-transpose of the user’s channel vector h□, yielding an output of the form: [23]

$$\mathbf{SINR_{mrc,k}} = \frac{\mathbf{pu\|h_k\|^4}}{\mathbf{p_u \sum_{i\neq k}^{k} h_k{}^H H_i + \|h_k\|^2}} \qquad \textbf{II.4}$$

II.2.2. Channel Estimation:

Massive MIMO systems rely on precise Channel State Information (CSI) for signal detection and decoding, as CSI captures the combined effects of fading and scattering on the communication link. In Frequency Division Duplexing (FDD) systems, CSI is estimated separately for uplink and downlink using pilot signals—a process that becomes overly complex with many antennas while Time Division Duplexing (TDD) simplifies this by exploiting channel reciprocity, allowing the base station to use uplink pilot signals to estimate downlink CSI and subsequently beamforming data to users. Despite TDD’s advantages, challenges such as pilot contamination from limited orthogonal pilots and increased hardware and computational demands persist, prompting the development of various channel estimation algorithms including Least Squares (LS), Minimum Mean Square Error (MMSE), deep neural networks, blind estimation, compressed sensing, and iterative approaches to optimize performance in massive MIMO systems, with ongoing research also exploring FDD adaptations [19].

II.2.2.1 Channel estimation methods for massive MIMO

Channel estimation is essential in massive MIMO systems to enable efficient beamforming and multi-user communication. Due to the large number of antennas, traditional estimation methods face scalability issues, so specialized techniques have been developed:

A. Pilot based channel estimation

In the pilot-based channel estimation, known pilot signal sequences are transmitted from each UT to the BS. By using these pilot signal sequences, channel coefficients between the BS and UTs can be estimated. MIMO systems that use pilot-based channel estimation methods send pilot signal sequences periodically so that channel estimates can be updated continuously as the CSI changes. The LS channel estimation method is one of the most common pilot-based channel estimation methods. It minimizes the squared distance between the received symbols vector and the transmitted symbols vector [24]. The LS estimate of the channel is given as in the following:

$$\boldsymbol{H_{LS}} = \boldsymbol{Y_P}\,(\boldsymbol{S_P^T}\,\boldsymbol{S_P})^{-1}\boldsymbol{S_P^T} \qquad \textbf{II.5}$$

where $\mathrm{H_{LS}} \in \mathbb{C}^{\mathrm{M*N}}$ is a matrix of the estimated complexchannel coefficients with LS between the M antennas of theBS and N UTs, $\mathrm{Y_P} \in \mathbb{C}^{\mathrm{M*P}}$ is a matrix of the P received pilotsymbols at the M receive antennas of the BS, $\mathrm{S_P} \in \mathbb{C}^{\mathrm{M*N}}$ is amatrix of the P transmitted pilot symbols from N users.[25]

B. Blind channel estimation:

Blind channel estimation infers channel coefficients from received signals' statistics without pilot signals, minimizing pilot contamination. It includes subspace-based and recursive methods. Subspace-based approaches leverage signal properties like finite alphabets and correlations over data blocks, while recursive methods adapt estimates per sample but require high memory, posing challenges for massive MIMO. Independent Component Analysis (ICA), a key subspace technique, estimates channels by maximizing signal independence. It involves SVD of the covariance matrix to separate signal and noise subspaces, whitening signals to ease computation, and constructing an orthogonal matrix to minimize mutual information. The fast ICA algorithm iteratively refines this matrix to achieve signal separation, finalizing the channel estimate with additional steps to correct phase and amplitude ambiguities. [25]

C. Semi-blind channel estimation:

Semi-blind channel estimation addresses the pilot contamination problem in massive MIMO by using shorter pilot sequences than conventional pilot-based methods, thereby reducing contamination while avoiding the high computational complexity of purely blind methods. While blind estimation methods like ICA-based approaches use SVD to extract the signal subspace—which is computationally demanding due to the large numbers of antennas—in semi-blind techniques, SVD is applied to the covariance matrix to span the left singular vectors corresponding to the user terminals, and any resulting ambiguity is resolved with pilot signals. This approach offers a more efficient trade-off between estimation accuracy and computational complexity. [26]

$$\mathbf{H_{SVD}} = \mathbf{U_S U_S^T H_{LS}} \qquad \mathbf{II.6}$$

Massive MIMO systems operate in multicell environments where each terminal uses a unique training sequence to minimize intra-cell interference, but the limited number of orthogonal sequences forces reuse across cells, leading to pilot contamination. This contamination occurs when identical pilot sequences from different cells result in inaccurate channel estimates and misdirected precoding, which degrades the overall signal-to-interference-plus-noise ratio (SINR) and ultimately saturates performance as the number of base station antennas increases. To mitigate these issues, various methods have been proposed, including blind and semi-blind techniques such as eigenvalue decomposition (EVD) approaches, iterative least-squares with projection, and coordinated training sequence assignments among cells, all of which aim to reduce inter-cell interference and enhance channel estimation accuracy while balancing computational complexity. [25]

II.2.2.2 Role of TDD and FDD in channel estimation:

Massive MIMO systems require accurate channel knowledge at the base station due to spatial multiplexing. In the uplink, users send training sequences to help the base station estimate their channel responses. However, in the downlink, obtaining precise channel information is more challenging because the base station must know the forward channel in advance as shown in the figure II.3. TDD systems address this by assuming channel reciprocity—using the uplink channel estimates for downlink transmissions after calibration—while FDD systems, lacking reciprocity, must rely on a closed-loop feedback process where the base station sends training sequences and receives limited channel state information (CSI) feedback from the users.

In TDD, the number of training sequences is equal to the number of users, making it scalable for massive MIMO. In contrast, FDD requires training sequences proportional to the number of base station antennas, which becomes impractical with large antenna arrays due to increased resource consumption, orthogonality constraints on pilots, feedback overhead, and potential CSI degradation from quantization errors and delays. Consequently, TDD is generally favored in massive MIMO systems, although FDD may be used if a reduced CSI accuracy is acceptable.

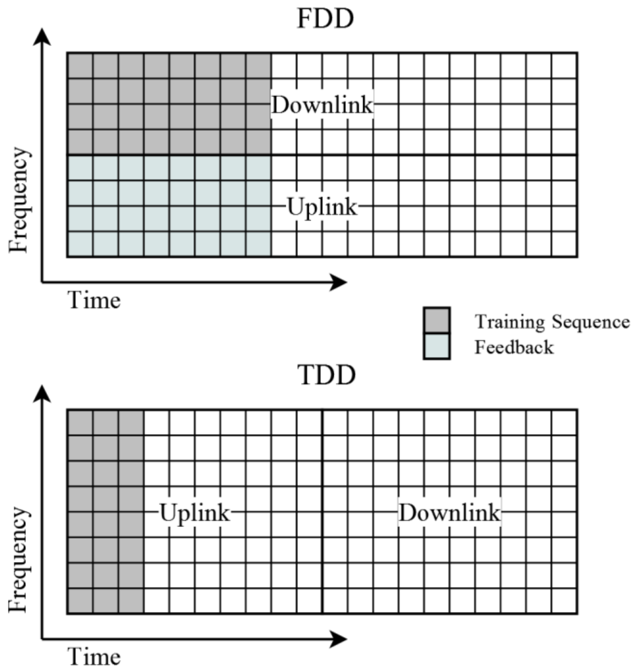

Figure II.3: Time slot with channel estimation for FDD and TDD systems.

II.2.2.3 Pilot contamination problem:

In massive MIMO, the base station estimates the uplink channel by having each user send a unique pilot sequence; by exploiting TDD reciprocity, it then infers the downlink channel. Because the pool of mutually orthogonal pilots is limited, pilots must be reused across cells, causing the BS to receive a mixture of its own users' channels plus those from neighboring cells as shown in the figure II.4. this is "pilot contamination," which caps system throughput and leads to unintended beamforming toward users in other cells.

A variety of techniques have been proposed to combat this: enhanced pilot-based estimators that leverage large antenna arrays; subspace methods that need fewer orthogonal pilots; pilot-reuse and partial-reuse schemes; contamination-aware precoding; blind (nonlinear) decontamination algorithms; and optimized pilot-assignment or reuse-factor strategies tailored to the user environment. Each can mitigate—though not wholly eliminate—the impact of pilot contamination in massive MIMO networks. [27]

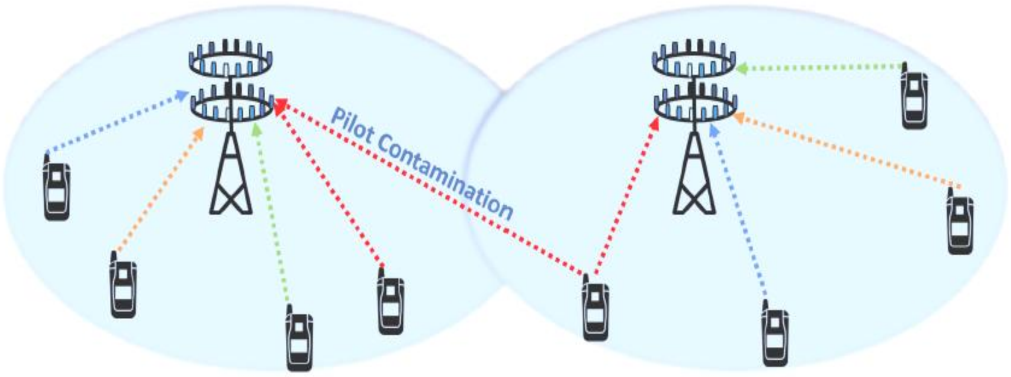

Figure II.4. Massive MIMO pilot contamination effect. [11]

II .2.3. Beamforming:

II .2.3.1 Concept and beamforming techniques:

Beamforming is the ability of the base station to adapt the radiation pattern of the antenna [19]. Beamforming helps the base station to find a suitable route to deliver data to the user, and it also reduces interference with nearby users along the route Beamforming has several advantages for 5G networks and beyond. Depending upon the situation, beamforming technology can be implemented in several different ways in future networks. For massive MIMO systems, beamforming helps with increasing spectrum efficiency, and for millimeter waves, it helps inboosting data rate. In massive MIMO systems, the base station can send data to the user from various paths, and beamforming here choreographs the packet movement and arrival time to allow more users to send data simultaneously as shown in the figure II.5. Since the millimeter waves cannot penetrate through obstacle sand do not propagate to longer distances due to a shorter wavelength, beamforming here helps tos end concentrated beams towards the users. Thus, beamforming helps a user to receive a strong signal without interference with other users. [19]

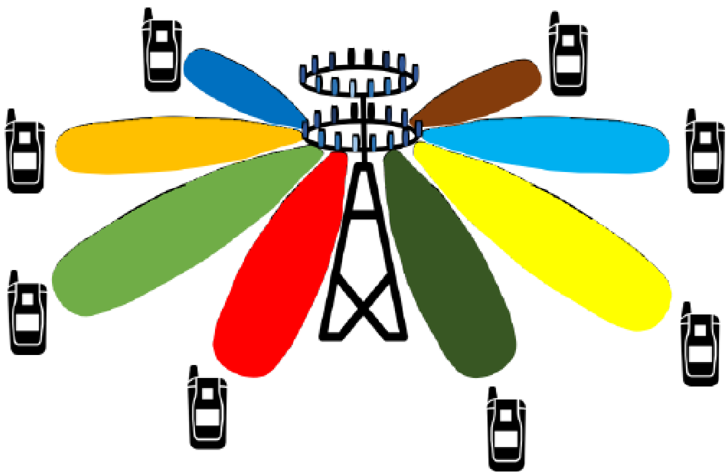

Figure II.5. Massive Multiple Output–Multiple Output (MIMO) beamforming. [11]

II .2.3.2 Types of beamforming techniques

Beamforming is a signal processing technique used in multi-antenna systems to direct signal transmission or reception toward desired directions. It plays a critical role in improving signal quality, range, and interference management. The main types include:

A. Analog beamforming

Analog beamforming transmits a single data stream using an RF chain equipped with multiple analog phase shifters, with all spatial processing occurring in the analog domain of both the transmitter and receiver. This technique adjusts the phase of each signal via low-cost phase shifters and typically employs a selective RF switch to control the beam's steering angle. Although its simple hardware design makes it cost-effective and relatively easy to implement, its inability to modulate signal amplitudes—only the phases—results in notable antenna gain loss and diminished overall performance. Consequently, despite its straightforwardness, analog beamforming is generally unsuitable for advanced applications like Massive MIMO and millimeter-wave systems where superior performance is required. [28]

B. Digital beamforming

Digital beamforming employs digital techniques—including DOA estimation, programmable control of antenna radiation patterns, and adaptive beam steering with nulling—to enhance the signal-to-noise ratio. This method allows for precise adjustment of both the phase and amplitude of signals, resulting in superior overall antenna performance that is difficult to achieve with analog methods. However, since digital beamforming operates at the baseband level, it requires that each antenna element be paired with its own dedicated RF chain (comprising components such as digital-to-analog converters, mixers, and power amplifiers), which makes its implementation in Massive MIMO systems considerably expensive due to the large number of antenna elements involved. [28]

C. Hybrid Beamforming

Hybrid Beamforming is a technique that integrates both analog and digital methods to optimize antenna performance. In this approach, digital processing generates the baseband signals while the analog portion manages RF chain effects, such as by reducing the number of required ADCs/DACs, thereby lowering costs. This method combines the cost-effective simplicity of analog beamforming with the precise phase and amplitude control of digital beamforming, which leads to enhanced amplifier performance and a more streamlined mixer design. In the literature there are various researches that demonstrated that hybrid beamforming is widely used in Massive MIMO systems, achieving performance close to full digital beamforming but at a reduced cost [29]. Moreover, recent studies have focused on adapting hybrid beamforming for millimeter-wave (mm Wave) bands in Massive MIMO, aiming to simplify complexity, improve routing accuracy, and efficiently handle wideband communication channels [28].

II.2.4. Intelligent Reflecting Surfaces (IRS) in Massive MIMO Systems

Intelligent Reflecting Surfaces (IRS) are a novel, passive, and programmable meta surface technology proposed for enhancing wireless communication, particularly in high-frequency bands such as millimeter-wave (mmWave) and Terahertz. IRS consists of numerous meta-atoms that can intelligently reflect incident electromagnetic waves without performing any active signal processing or introducing delay, thereby acting as intelligent scatterers in the physical environment. In the context of Massive MIMO systems, IRS can effectively manipulate the wireless channel to improve coverage, mitigate signal blockages, and enhance spectral efficiency. By enabling cost-effective and energy-efficient reconfiguration of propagation environments, IRS plays a critical role in overcoming the limitations of direct links in blocked or highly attenuated channels, especially in future 6G networks. [30]

II.2.4.1 The role of intelligent reflecting surface sin massive MIMO

With the ever-growing demand for high-speed and reliable wireless communication, researchers have been looking for innovative ways to enhance network performance. One of the promising technologies that have emerged is Intelligent Reflecting Surfaces (IRS). This technology aims to control the wireless environment actively by using passive, reconfigurable elements to manipulate radio signals and direct them toward users.

In Massive MIMO (Multiple-Input Multiple-Output) systems, where a large number of antennas are used at the base station to improve spectral efficiency, IRS serves as a game-changing solution to combat signal degradation in environments with obstacles, such as urban settings or indoor deployments. By leveraging IRS, wireless networks can redirect signals dynamically, minimize interference, and improve overall network efficiency—all while maintaining energy efficiency as shown in Figure II.6 and Figure II.7. [31]

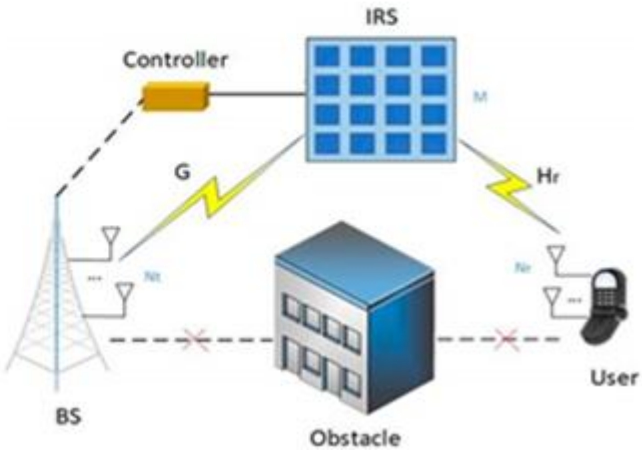

Figure II.6: Reconfigurable Intelligent Surface (IRS)-Enabled Signal Redirection. [31]

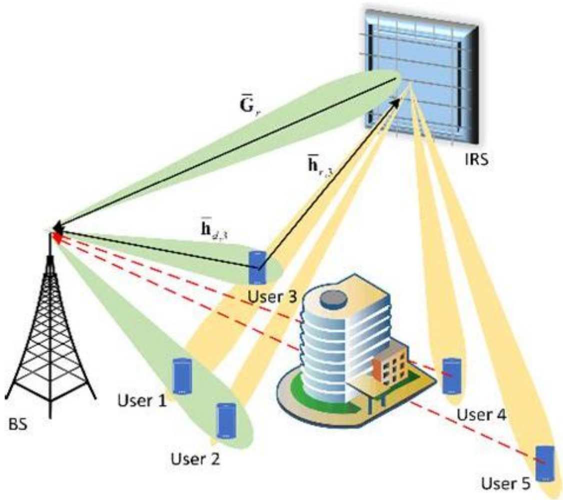

Figure II.7: Intelligent Reflecting Surface (IRS)-Aided Wireless Communication System.[31]

II.2.4.2 IRS Operating Principles and Channel Model

Intelligent Reflecting Surfaces (IRS) operate based on passive reflection and intelligent phase control. Each meta-atom on the IRS is a purely reflective element without any active circuitry, amplifiers, or RF chains, enabling zero-delay reflection of incident waves and significantly reducing power consumption and hardware cost. The reflection phase of each element is governed by a central controller, which uses channel state information (CSI) to set phase shifts that direct reflected waves toward intended users, achieving passive beamforming without additional energy expenditure. The IRS-assisted communication channel is modeled as a product-distance path-loss model, where the base station (BS) to IRS and IRS to user links each incur distance-dependent path loss, characterized by their respective distances and path-loss exponents. In a centralized deployment, a single IRS with meta-atoms supports communication between a BS with antennas and single-antenna users. In contrast, a distributed deployment involves independent IRS units, each with elements, centrally coordinated to share CSI and synchronize phase shifts. This configuration enables flexible and scalable coverage. A major limitation in mmWave systems is the low rank of single-path line-of-sight (LoS) cascaded channels, which hinders multi-user multiplexing. This can be overcome by combining multiple rank-1 cascaded channel matrices with independently configured phase shifts, resulting in a full-rank aggregate channel. This strategy enables sufficient degrees of freedom to support simultaneous communication with multiple users, greatly improving spatial multiplexing performance. [32]

II.2.5. Number of Antennas in Massive MIMO Systems

II.2.5.1 Definition and Concept

The number of antennas at the base station is a fundamental design parameter in Massive MIMO systems. It defines the architectural structure of the system and enables the implementation of advanced communication techniques such as spatial multiplexing and beamforming. A system is typically considered 'massive' when the number of antennas exceeds a certain threshold, determined by system requirements and the type of wireless service.

II.2.5.2 Theoretical Dimensions of the Number of Antennas

- Spatial Multiplexing: The system leverages the spatial structure of the antenna array to separate transmitted and received signals in space, which allows for multiple simultaneous data streams over the same frequency band.
- Beamforming: With a large number of antennas, the base station can dynamically form and direct narrow beams toward specific users, enhancing the system's spatial selectivity.
- Diversity: A higher number of antennas allows the system to exploit spatial diversity in the wireless channel, which theoretically leads to improved connection stability and reliability, without specifying any quantitative effect.[33]

II.2.5.3 Challenges Related to Increasing the Number of Antennas

- Channel State Information (CSI) Estimation: A larger antenna array necessitates advanced algorithms for channel estimation, to efficiently process the increased volume of data generated by the system.
- Pilot Contamination: In multi-cell systems, reusing pilot sequences can introduce interference known as pilot contamination, which poses a unique challenge as the number of antennas increases. Addressing this issue requires innovative planning and algorithmic solutions.
- Hardware and Cost: Large-scale antenna systems demand advanced hardware infrastructure and higher computational capabilities, impacting the overall system complexity and cost.

II.2.5.4 Research Directions and Modern Techniques

- Antenna Number Modulation (ANM): Among the latest research trends, ANM involves exploiting the activation pattern of antennas as an additional means of information encoding, thus opening new possibilities for communication system design.
- Antenna Grouping: Grouping antennas into blocks or clusters provides increased flexibility in resource allocation and system configuration, paving the way for more dynamic and adaptable wireless systems.[34]

II.2.6 Conclusion

In this chapter, we studied various techniques that impact spectral efficiency (SE). In the next chapter, we will focus on precoding techniques, presenting a comparative study among them while analyzing how the number of antennas affects SE under different scenarios.

Chapter III: Simulation and results

III .1 Introduction

In this chapter, we investigate the impact of three key factors on the spectral efficiency (SE) performance of Massive MIMO systems: the number of antennas, the choice of precoding techniques, and the presence of pilot contamination. These parameters play a central role in shaping the performance of practical wireless systems. Increasing the number of antennas enhances spatial multiplexing capabilities and can significantly improve SE, although with potential limitations in hardware and channel conditions. Precoding techniques are also examined, as they help manage inter-user interference and improve signal quality. We compare different precoding methods to assess their effectiveness and computational complexity. Additionally, we analyze the effect of pilot contamination, a major challenge in multi-cell systems, which can degrade channel estimation accuracy and reduce SE. All simulations are performed using MATLAB software to evaluate system performance under various configurations and provide meaningful insights into the trade-offs and limitations involved.

III.2 Channel Model

It is important to note that we use Rician channel in our simulation.

Rician fading or Ricean fading is a stochastic model for radio propagation anomaly caused by partial cancellation of a radio signal by itself — the signal arrives at the receiver by several different paths (hence exhibiting multipath interference), and at least one of the paths is changing (lengthening or shortening). Rician fading occurs when one of the paths, typically a line of sight signal or some strong reflection signals, is much stronger than the others. In Rician fading, the amplitude gain is characterized by a Rician distribution.

Rayleigh fading is sometimes considered a special case of Rician fading for when there is no line of sight signal.

III.2.1 Mathematical Model of Rician Channel:

$$\boldsymbol{h}(\mathbf{t}) = \sqrt{\frac{K}{K+1}}\,.\,\boldsymbol{h}_{Los}(\boldsymbol{t}) + \sqrt{\frac{1}{K+1}}\,.\,\boldsymbol{h}_{NLos}(\boldsymbol{t}) \qquad \textbf{III.1}$$

Where:

- h(t): Complex channel coefficient at time t
- $h_{los}\,(t) = \; e^{j(2\pi f_D t+\phi)}: Deterministic\ los\ componet$
- $f_D: Doppler\ shift$
- $\phi: Phase\ shift$
- $h_{Nlos}(t): Complex\ Gaussian\ process\ representing\ the\ scattered$ (Rayleigh)$component$
- K: Rician k-factor (ratio of Los power to scattered power).

The Rician fading channel is modeled as a combination of a deterministic Line-of-Sight (LoS) component and multiple scattered Non-Line-of-Sight (NLoS) components. The complex baseband representation is given by:

In a Rician fading channel, the K-factor (or Rician K-factor) is a measure of the strength of the Line-of-Sight (LoS) component relative to the scattered multipath components.

$$K=\frac{\text{power of Los component}}{\text{Power of scatterd (NLOS)components}}$$

- ✓ K = 0 → No LoS path → the channel becomes a Rayleigh fading channel.
- ✓ K > 0 → There is a dominant LoS component.
- ✓ K → ∞ → Only LoS, no fading → a pure AWGN channel (ideal case).
- A higher K means more reliable communication with less fading (e.g., satellite links, openruralareas).
- A lower K (close to 0) indicates strong fading (e.g., urban environments with many obstacles).

When the Rician K-factor is less than 0 dB, it means the power of the Line-of-Sight (LoS) component is weaker than the power of the scattered multipath components.

III.3 Spectral efficiency with number of antennae

The primary objective of this section is to analyze the relationship between the number of base station antennas (M) and total spectral efficiency in Massive MIMO systems.

III.3.1 Simulation Parameter

The following table III.1 presents the main simulation parameters and the spectral efficiency formula used in this part of the study. It details the range of base station antennas, the SNR value, the number of user antennas, and the formula applied to calculate spectral efficiency. This overview highlights how varying the number of base station antennas influences the spectral efficiency in Massive MIMO systems.

The table III.1 Simulation Parameters for Analysing the Effect of BS Antenna Numbers on Spectral Efficiency.

Number of antennae	10 to 200
SNR [dB]	10
User antenna	1
Spectral Efficiency formula	$SE = \log_2 \left(1 + \frac{M.SNR}{K}\right).K$
Performance Metric	Total Spectral Efficiency (bits/s/Hz)

Table III.1:Simulation Parameters for Analysing the Effect of BS Antenna Numbers on Spectral Efficiency

The figure III.1 represents the results of Spectral Efficiency (SE) in terms of the number of base station antennas (M) for different numbers of antennas in Massive MIMO systems.

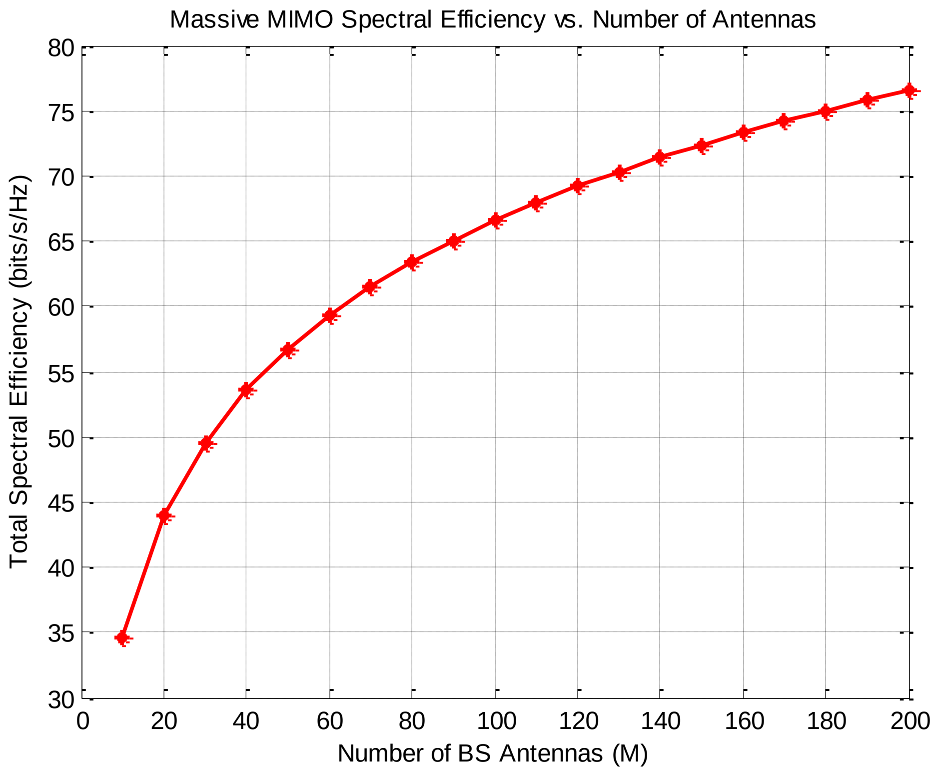

Figure III.1: spectral efficiency Vs number of antennae.

III.3.2 Analysis

Figure III.1 illustrates the relationship between the number of base station (BS) antennas and the total spectral efficiency in a Massive MIMO system. As the number of antennas increases from 10 to 200, the spectral efficiency improves markedly from approximately 35 bits/s/Hz to nearly 78 bits/s/Hz. This trend highlights the capacity of Massive MIMO to significantly boost network throughput through spatial multiplexing.

However, the curve in the figure clearly shows a diminishing return in performance gains as the number of antennas close to 200. While initial increments in antenna count yield substantial improvements, the rate of growth in spectral efficiency slows down beyond around 120 antennas.

This saturation is primarily due to inter-stream interference, which becomes more pronounced as more data streams are transmitted simultaneously. Without adequate interference mitigation, this can severely limit performance. To counter this, advanced signal processing techniques such as beamforming and precoding are employed. These methods enhance signal integrity and minimize interference, allowing systems with large antenna arrays to maintain high spectral efficiency.

Overall, these results demonstrate that while adding antennas is beneficial, optimal system design must also address interference management. Massive MIMO, with its advanced capabilities, remains a cornerstone technology for achieving the high data rates required in 5G and future wireless communication systems.

III.4 Spectral Efficiency with number of antennas for different users

The primary objective of this section is to analyze the relationship between the number of base station antennas (M) and total spectral efficiency in Massive MIMO systems for different numbers of users (K).

III.4.1 Simulation paramater

The following table III.2 summarises the simulation parameters and the spectral efficiency formula adopted in this study. It outlines the range of values considered for the number of users and base station antennas, as well as the performance metric and main assumptions used for analysing Massive MIMO system efficiency.

The Table III.2 Simulation Parameters for Evaluating Spectral Efficiency versus Users and Antennas.

Number of Users (K)	5, 10, 20, 40
Number of BS Antennas (M)	10 to 500
Performance Metric	Total Spectral Efficiency (bits/s/Hz)(
SE Formula	$SE = log_2 \ = 1 + \frac{M.SNR}{K} \ .\mathrm{K}$
SNR [dB]	10

Table III.2: Simulation Parameters for Evaluating Spectral Efficiency versus Users and Antennas

The figure III.2 represents the results of ES in terms of the number of antennas using different users (K).

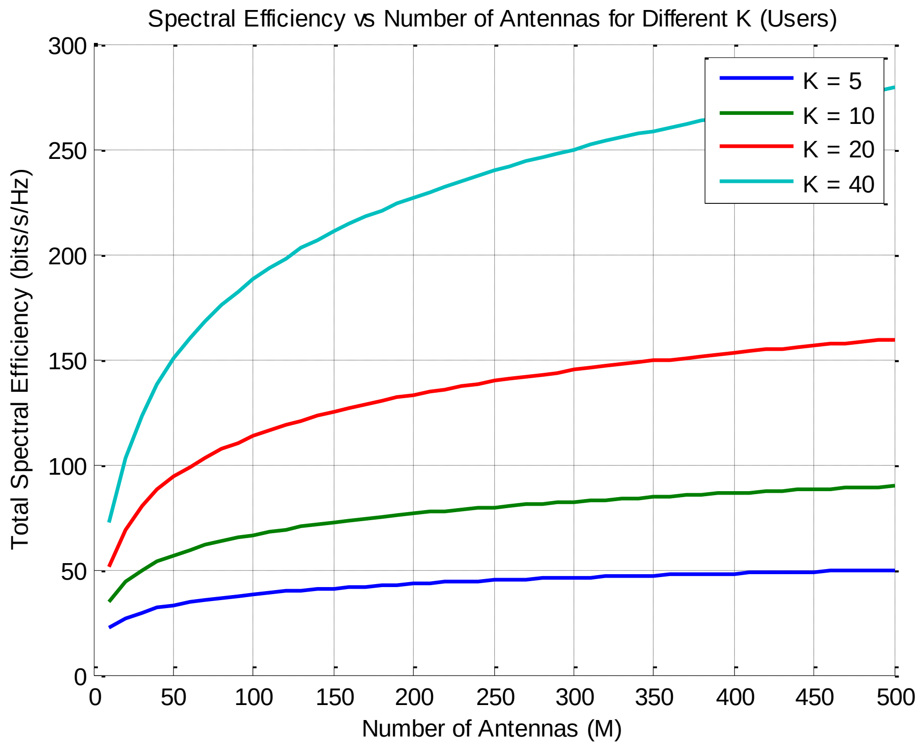

Figure III .2: Spectral Efficiency Vs Number of Antennas for Different K (Users)

III.4.2 Analysis

- **Case 1: K = 5**

When the number of users is low (K = 5), spectral efficiency shows a rapid improvement with the increase in the number of antennas (M), especially when.

M < 150. However, the growth slows down significantly after M ≈ 200, and the curve stabilizes around M ≈ 300. This behavior is due to low interference between users, allowing high efficiency even with a moderate number of antennas. Beyond a certain point.

- **Case 2: K = 10**

When the number of users increases to K = 10, the spectral efficiency starts at a higher baseline compared to K = 5 and grows steadily until M ≈ 250. After that, the growth slows down. This reflects better utilization of spectral resources due to user diversity, which mitigates selective fading effects. However, after M ≈ 250, the system shows signs of limitation, such as the complexity of multi-channel estimation and co-channel interference. This highlights the importance of balancing the number of antennas and users.

- **Case 3: K = 20**

With 15 users (K = 15), there is a continuous improvement in spectral efficiency as the number of antennas increases. The efficiency starts to improve significantly from M ≈ 50 and continues to grow until M ≈ 300, thanks to techniques like beamforming. As more antennas are added, the performance improves, but at a certain point (M ≈ 300), the growth starts to slow down.

- **Case 4: K = 40**

At 20 users (K = 20), the system demonstrates significant improvements in spectral efficiency. The curve starts high (M ≈ 50) and continues to grow nearly linearly until M ≈ 400. This improvement is due to the efficient use of spatial diversity across antennas. However, after M ≈ 400, the growth slows down as the system approaches the theoretical capacity limit, and further antenna additions offer minimal benefit without optimizing other factors.

III.5 Impact of Pilot Contamination on Spectral Efficiency (with or without)

The primary objective of this section is to analyze spectral efficiency in Massive MIMO systems by examining the relationship between the number of base station antennas (M) and the total spectral efficiency, while highlighting the challenges of pilot contamination (with or without).

III.5.1 Simulation Pramater

The following table III.3 summarises the main simulation parameters and the spectral efficiency formulas used to evaluate the performance of Massive MIMO systems with and without pilot contamination. It includes the values considered for the number of users, base station antennas, SNR, and the specific expressions applied in each scenario. This comparison aims to highlight the impact of pilot contamination on total spectral efficiency.

The table III.3 Simulation Parameters and Spectral Efficiency Formulas with and without Pilot Contamination

SNR [dB]	10
Number of Users (K)	10
Number of BS Antennas (M)	10 to 500
SINR (with PC)	$\frac{M}{K^2 - 1 + \sigma}$
SE Formula (no PC)	$SE = log_2 1 + \frac{M.SNR}{K}.K$
SE Formula (with PC)	$SE = log_2 1 + \frac{M}{K^2 - 1 + \sigma}.K$
Performance Metric	Total Spectral Efficiency (bits/s/Hz)

Table III.3: Simulation Parameters and Spectral Efficiency Formulas with and without Pilot Contamination

The figure III.3 represents the results of Spectral Efficiency (SE) in terms of the number of base station antennas (M) with and without pilot contamination in Massive MIMO systems.

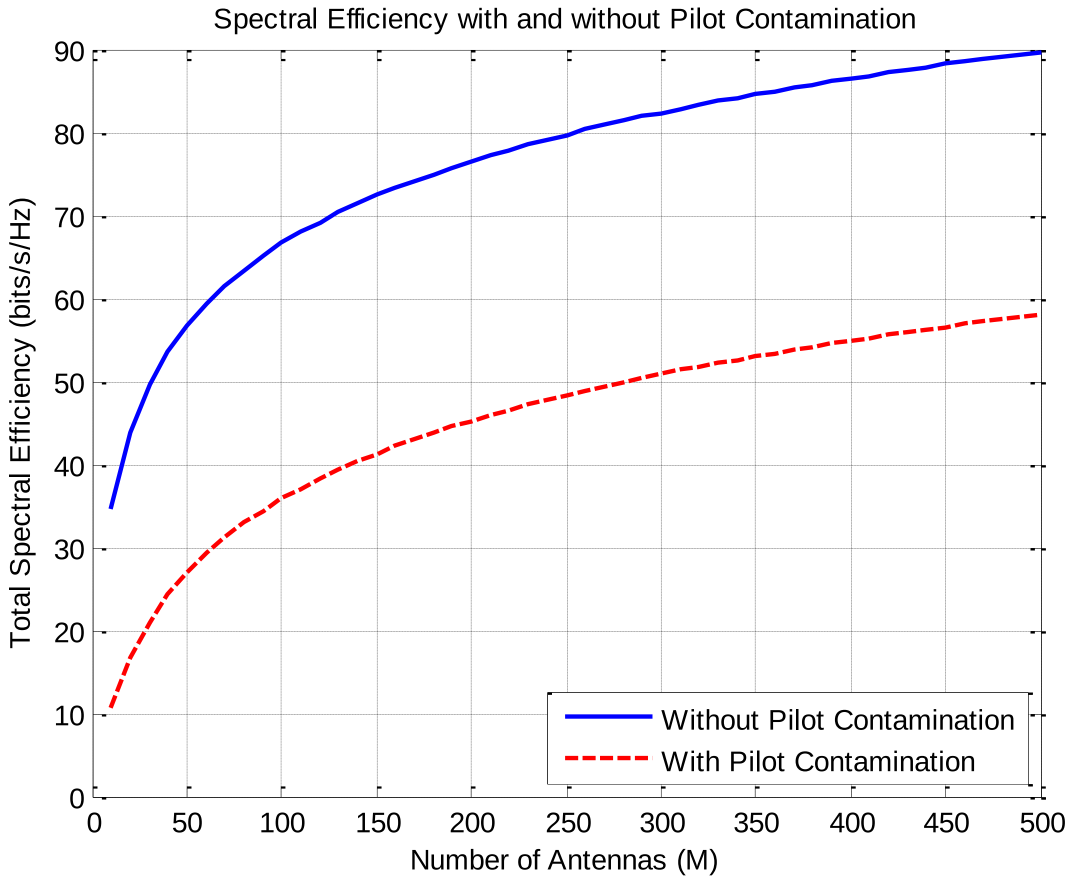

Figure III .3 Spectral Efficiency with and without Pilot Contamination

III.5.2 Analysis:

Without pilot contamination, spectral efficiency increases almost linearly as the number of antennas grows (from 50 to 500). This is due to the system's enhanced capability to perform precise beamforming and leverage spatial diversity, which together lead to significantly higher capacity—reaching up to approximately 80 bit/s/Hz with 500 antennas

With pilot contamination, the growth in spectral efficiency slows down significantly as the number of antennas increases. Although performance still improves to some extent, the interference caused by pilot reuse across neighboring cells degrades channel estimation accuracy. This limits the effectiveness of beamforming and results in saturation of spectral efficiency, typically occurring around 300 to 400 antennas, far below the potential seen in ideal conditions.

III.6 Spectral efficiency and precoding ZF MRT and MMSE

The primary objective of this section is to analyze spectral efficiency in Massive MIMO systems by examining the relationship between the number of base station antennas (M) and the total spectral efficiency, while comparing different precoding techniques (MRC, ZF, MMSE)

III.6.1 Simulation Pramater

The following table III.4 outlines the key simulation parameters and conditions used to evaluate spectral efficiency under different precoding techniques in Massive MIMO systems. The analysis considers variations in the number of base station antennas, Rician K-factors, and detection schemes, as well as a Rician fading channel model. This setup aims to investigate the impact of these parameters on spectral efficiency when using MRC, ZF, and MMSE detection methods.

The table III.4 Simulation Parameters for Spectral Efficiency Analysis Using Different Precoding Techniques under Rician Fading.

Parameter	Value
SNR [dB]	0
BS Antennas (M)	1 TO 40
Number of Realizations	1000
Rician K-factors [dB]	[0] [-40]
Detection Schemes	MRC (red), ZF (blue), MMSE (green)
Channel Model	Rician fading: LOS + NLOS components
Performance Metric	Spectral Efficiency in(bits/s/Hz)
Number of Users (K)	2

Table III.4: Simulation Parameters for Spectral Efficiency Analysis Using Different Precoding Techniques under Rician Fading

The figure III.4 represents the results of Spectral Efficiency (SE) in terms of the number of base station antennas (M) using different precoding techniques (MRC,Z, MMSE) at K= 0dB.

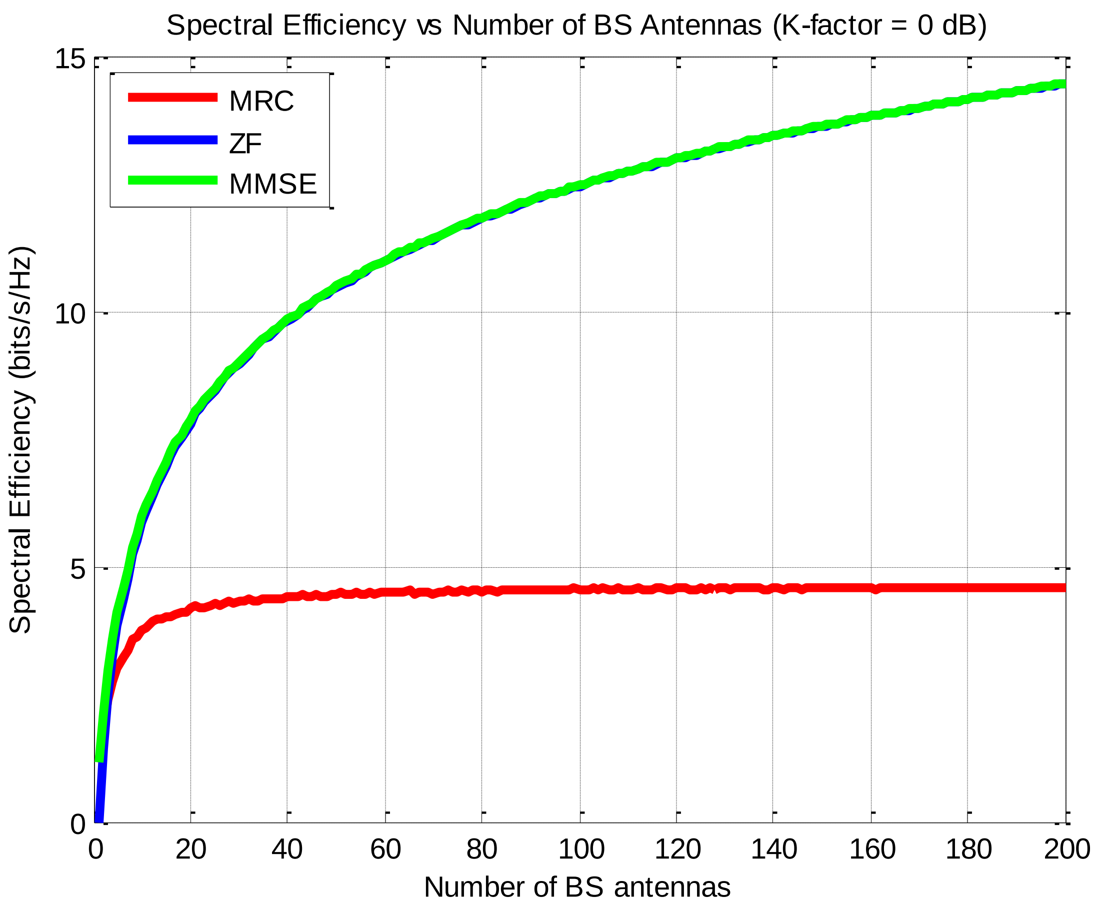

Figure III 4: The spectral efficiency versus the number of BS antennas for MRC, ZF, MMSE and K= 0 dB

III.6.2 Analysis

- **Case K = 0 dB**
  - ✓ **MRC:** Under a clear LoS component, MRC starts at about 1.2 bits/s/Hz with 2 antennas, rising to 3.8 bits/s/Hz at 10 antennas thanks to increased array gain and spatial diversity. As more antennas are added, residual inter-user interference grows, causing the curve to plateau around 4 bits/s/Hz beyond 20 antennas, where additional antennas no longer yield significant gains.
  - ✓ **ZF:** ZF begins at approximately 3.2 bits/s/Hz for 5 antennas, climbs to 6.0 bits/s/Hz at 10 and 8.0 bits/s/Hz at 20 by effectively canceling inter-user interference, but noise amplification inherent in its matrix inversion slows further growth, leading to a plateau near 9.8 bits/s/Hz at 40 antennas.
  - ✓ **MMSE:** By optimally balancing interference suppression with noise minimization, MMSE outperforms the others—starting at 1.8 bits/s/Hz at 2 antennas, reaching 6.5

bits/s/Hz at 10 and 8.3 bits/s/Hz at 20, then continuing to climb to around 10.0 bits/s/Hz at 40 antennas without clear saturation.

The figure III.5 represents the results of Spectral Efficiency (SE) in terms of the number of base station antennas (M) using different precoding techniques (MRC, ZF, MMSE) at K= 0 dB.

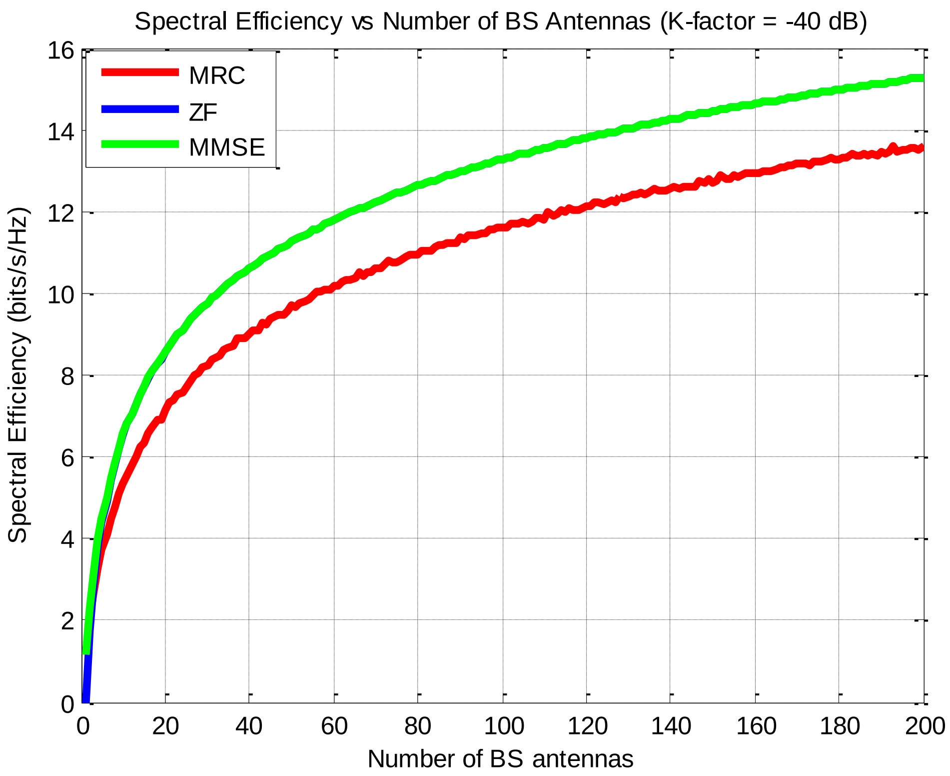

Figure III .5: The spectral efficiency versus the number of BS antennas for MRC, ZF, MMSE and K= -40 dB

- **Case K = –40 dB**
  - ✓ **MRC:** With LoS removed, MRC starts at about 1.5 bits/s/Hz at 2 antennas—higher than in the LoS case—thanks to reduced direct-path interference and richer multipath diversity. It then increases to roughly 5.5 bits/s/Hz at 10 antennas and 7 bits/s/Hz at 20 antennas, but plateaus around 7.8 bits/s/Hz after about 25 antennas as residual interference limits further gains.
  - ✓ **ZF:** ZF benefits from the absence of LoS interference, yielding about 4.0 bits/s/Hz at 5 antennas, jumping to 7.0 bits/s/Hz at 10 and 8.5 bits/s/Hz at 20 antennas. However, noise amplification during the matrix inversion slows its later growth, capping performance near 10.5 bits/s/Hz at 40 antennas before the curve begins to flatten.
  - ✓ **MMSE:** MMSE leverages both multipath diversity and balanced noise suppression to outperform the others. It starts at 4.3 bits/s/Hz at 5 antennas, climbs to 7.5

bits/s/Hz at 10 and 9.0 bits/s/Hz at 20, and continues rising to about 11.0 bits/s/Hz at 40 antennas with no clear saturation, reflecting its optimal trade-off between interference cancellation and noise resilience.

III.7 Conclusion

In this chapter, we studied the impact of the number of antennas, precoding techniques, and pilot contamination on spectrum utilization efficiency in Massive MIMO systems. The results show that increasing the number of antennas improves performance up to a certain limit, and pilot pollution reduces these improvements. The MMSE technique was also shown to be better at minimizing interference and increasing efficiency.

General Conclusion

General Conclusion

In this MIMO, Massive MIMO technology has been studied as a fundamental element in addressing the growing challenges of fifth-generation (5G) networks, particularly with respect to spectral efficiency and system capacity. Through detailed analysis, the impact of several key parameters such as the number of antennas, the number of users, precoding techniques (MRC, ZF, MMSE), and the effect of pilot contamination on system performance has been evaluated.

Simulation results confirmed that increasing the number of base station antennas leads to a significant improvement in spectral efficiency, primarily due to beamforming gains. However, these gains begin to diminish beyond a certain threshold, especially when interference or pilot contamination is not effectively managed.

The comparison of precoding techniques showed that MMSE offers the best trade-off between interference suppression and noise resilience, particularly in environments lacking a clear line-of-sight (NLoS). On the other hand, ZF demonstrates good performance but suffers from noise amplification at low SNR levels, while MRC is simpler to implement but less effective in high-interference user scenarios.

The study also highlighted the importance of Intelligent Reflecting Surfaces (IRS) as a complementary technology to Massive MIMO, particularly in improving coverage and spectral efficiency in complex and challenging propagation environments.

Overall, this study emphasizes that achieving optimal performance in practical Massive MIMO deployments requires a strategic integration of antenna configuration, advanced precoding, accurate channel estimation, and interference management.

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