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# Enhancing spectral efficiency in uplink/downlink channels of multi-cell massive MIMO for 5G networks

Rao Muhammad Asif [1], Ateeq Ur Rehman [2,*], Sghaier Guizani [3], Habib Hamam [4,5,6,7]

[1]Department of Electrical Engineering, Superior University, Lahore 54000, Pakistan
[2]School of Computing, Gachon University, Seongnam 13120, South Korea
[3]Electrical Engineering Department, Alfaisal University, Riyadh, Saudi Arabia
[4]Department of Electrical and Electronic Engineering Science, School of Electrical Engineering, University of Johannesburg, Johannesburg 2006, South Africa
[5]Faculty of Engineering, Uni de Moncton, Moncton, NB E1A3E9, Canada
[6]Faculty of Graduate Studies and Research, Hodmas University College, Taleh Area, Mogadishu, Somalia
[7]Sector of Research and Innovation, Bridges for Academic Excellence, Tunis, Centre-Ville 1002, Tunisia

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A B S T R A C T

Massive multiple-input multiple-output (MIMO) systems are at the forefront of 5G technology, significantly improving energy efficiency compared to earlier wireless communication systems. This study develops an optimal model for energy-efficient massive MIMO systems, aiming to increase spectral efficiency (SE) within a multi-cell framework. Base stations (BSs) use various techniques for channel estimations during uplink (UL) transmission, including minimum mean-squared error (MMSE), Least Squares, and Element-wise MMSE (EW-MMSE) estimators. The research evaluates the SE achievable through MMSE channel estimation by applying different receive combining schemes. Additionally, it explores downlink (DL) transmission using various precoding schemes, utilizing vectors similar to those in combining schemes. Simulations show a significant improvement in SE by advancing UL and DL transmission models. The study highlights that optimized MMSE channel estimation, along with an increased number of BS antennas and the ability to serve multiple user equipment (UEs) per cell, can enhance the average SE per cell. The findings indicate that optimizing channel estimation is crucial for the development of massive MIMO systems, especially for improving SE in both UL and DL transmissions.



## 1. Introduction

The relentless push towards the next generation of wireless communication systems is driven by a growing demand for higher data rates, improved network capacity, and enhanced user experiences. The evolution of 5G technology and its transition into 6G exemplifies this journey towards more sophisticated, efficient, and robust communication infrastructures. Central to this evolution is the development and optimization of massive multiple-input multiple-output (MIMO) systems, which emerged as a cornerstone technology for modern wireless communication due to their potential to significantly increase network capacity and spectral efficiency (SE) (Huo et al., 2023).

Massive MIMO systems, characterized by their use of several antennas at the base station to serve multiple users simultaneously, have been identified as key enablers for 5G networks and beyond. These systems promise substantial gains in SE and energy efficiency (EE) over traditional MIMO technologies. However, realizing these benefits in practical multi-cell scenarios presents complex challenges, including managing inter-cell interference, optimizing channel estimation, and designing efficient uplink (UL) and downlink (DL) transmission strategies (Alam et al., 2023).

The dynamic and dense nature of modern wireless networks, compounded by the ever-increasing user demands for data, necessitates a reevaluation and enhancement of massive MIMO system designs to address these challenges effectively. This research addresses several critical aspects of massive MIMO technology, particularly in multi-cell scenarios (Chataut and Akl, 2020). The

* Corresponding Author.
Email Address: 202411144@gachon.ac.kr (A. U. Rehman)
https://doi.org/10.21833/ijaas.2024.08.008
Corresponding author's ORCID profile:
https://orcid.org/0000-0001-5203-0621

real-world applicability and potential impact on existing 5G systems are also highlighted:

- Realistic performance evaluation: Our model considered inter-cell interference and noise, encouraging massive MIMO networks to perform real-world scenarios enhancing reliability.
- Channel estimation: We evaluate different schemes, suggesting MMSE estimators for superior SE. Implementing these insights in 5G systems could lead to more efficient spectrum usage and improved quality of service for users.
- DL enhancement: We Propose a novel MR precoding model for better SE, potentially improving data rates and performance for users. This is valuable for applications requiring high throughput, such as video streaming or virtual reality.

On the other hand, existing 5G systems can be upgraded by enhancing SE and interference management with our proposed model. It can lead to higher data rates and better user experience. In addition, optimizing resource utilization can accommodate more users and devices without sacrificing performance.

The research presented in this article focuses on several key aspects and introduces novel elements aimed at advancing the state of massive MIMO technologies, specifically in the context of multi-cell environments. The given objectives, accomplished through rigorous analysis and modeling, include:

- Multi-cell scenario consideration: The study addresses the complexities of UL and DL transmission models within a multi-cell setting, taking into account the pervasive issues of inter-cell interference and environmental noises. This approach provides a realistic examination of massive MIMO systems' performance in scenarios that closely mimic real-world operational conditions.
- Channel estimator modeling: The work evaluates the efficacy of various channel estimation schemes—namely, the minimum mean-squared error (MMSE), Least Squares (LS) as well as Element-wise MMSE (EW-MMSE) estimators—within the UL transmission framework. The MMSE estimator, in particular, is highlighted for its superior SE achievement and enhanced interference mitigation capabilities, positioning it as a preferable choice over EW-MMSE and LS in the context of maximizing SE.
- DL transmission enhancement: A novel Maximum Ratio (MR) precoding model is proposed for DL transmission to enhance SE. This model is designed to leverage the unique advantages of massive MIMO systems, optimizing the signal-to-interference-plus-noise ratio (SINR) and, by extension, the SE for users in a multi-cell environment.

By addressing these key aspects with novel contributions, the paper aims to push the boundaries of massive MIMO system performance, paving the way for more efficient, robust, and high-capacity wireless communication networks.

The outcomes derived from our proposed models substantiate the capability of massive MIMO systems to significantly bolster SE within 5G cellular networks. The structure of this paper is as follows: Section 1 introduces the context and motivation behind this research alongside the key aspects and novel elements it presents. Section 2 discusses related works, providing a survey of current research and identifying existing gaps that our study aims to address. Section 3 details the modeling of UL and DL transmissions within massive MIMO systems. Section 4 outlines the methodology and analytical framework employed in our study, delving into channel estimation and the SE enhancement techniques for both UL and DL communications. The results and their implications are thoroughly discussed in Section 5, which compares different channel estimators and their impact on UL SE and evaluates the performance of DL precoding schemes. Finally, Section 6 concludes the paper by summarizing our findings and contemplating prospects for future research that could build upon this study's contributions.

## 2. Literature survey

The basic elements of a paper are listed below in the order in which they should appear. The exploration of massive MIMO systems within the realm of 5G and beyond has garnered considerable attention from the research community, leading to a plethora of studies aimed at enhancing various facets of this technology. The significance of massive MIMO in the evolution of wireless communication systems cannot be overstated, with its potential to drastically improve both spectral and energy efficiencies being a focal point of contemporary research efforts. This attention stems from the technology's ability to leverage a large number of M at the BS to serve multiple users simultaneously, thereby increasing network capacity and efficiency.

### 2.1. Current research

In the domain of 5G networks, the role of massive MIMO is pivotal, with foundational principles suggesting its critical contribution to meeting the burgeoning demand for higher data rates and network reliability. Early research, as documented in studies (Liu et al., 2018; Khan et al., 2022; Asif et al., 2020), lays the groundwork by highlighting the theoretical and practical advantages of implementing massive MIMO technologies. These studies underscore the correlation between the number of antennas and enhanced system performance, illustrating the capacity for massive MIMO to facilitate exponential improvements in network throughput and user experience.

Channel estimation emerges as a critical area of focus in the quest to optimize massive MIMO system performance. The accuracy of channel estimation directly influences the system's ability to efficiently allocate resources and manage interference, which are essential for maintaining high levels of SE and reliability in densely populated network environments. Research efforts, as detailed in references (Chataut et al., 2019; Kang et al., 2017; Zahoor et al., 2022), delved into various channel estimation strategies, including but not limited to MMSE, EW-MMSE, and LS estimators. These approaches are scrutinized for their efficacy in real-world scenarios characterized by dynamic user mobility and fluctuating interference levels. Among these, the MMSE estimator is frequently highlighted for its ability to strike a favorable balance between computational demands and performance outcomes, making it a preferred choice for systems aiming to maximize SE while mitigating the adverse effects of interference.

The collective insights from these foundational studies pave the way for ongoing innovations in massive MIMO technology. By addressing the challenges associated with antenna design, channel estimation, and transmission optimization, the research community continues to advance the capabilities of 5G networks. The progression from theoretical models to practical applications signifies a critical phase in the evolution of wireless communication, with massive MIMO systems at the forefront of this transformation. Recent advancements in antenna design have significantly impacted the field of massive MIMO systems, addressing both the physical limitations and the stringent performance requirements imposed by modern wireless networks. A notable contribution by Palanisamy et al. (2024) showcased the development of a frequency-reconfigurable antenna tailored for 5G applications. Their approach, utilizing a hybrid metaheuristic framework, represents a leap forward in optimizing antenna configurations to meet the dual demands of flexibility and efficiency in frequency utilization. This innovation is particularly relevant in the context of 5G, where the ability to adapt to varying frequency bands can greatly enhance network performance and user satisfaction. Similarly, the work of Basir et al. (2023) introduces a monopole Ultra-Wide-Band (UWB) MIMO antenna characterized by its triple-notched features. This design specifically addresses the challenge of interference within densely populated spectrum environments, such as those encountered in 5G networks.

By incorporating notched characteristics at strategic frequencies, this antenna effectively minimizes potential signal overlap, thereby improving the clarity and reliability of wireless communication. Such advancements in antenna technology are crucial for the ongoing evolution of wireless systems, offering solutions that cater to the ever-increasing complexity and demands of 5G and beyond.

Recent advancements in artificial intelligence (AI) and machine learning (ML) for wireless communications mark a transformative phase in optimizing network operations and enhancing the overall user experience. Through the application of AI and ML, complex multiobjective optimization problems (MOOPs) associated with network management and resource allocation can be addressed more efficiently. In this vein, the research presented by Shafiei et al. (2021) explored the potential of AI-driven algorithms to solve MOOPs in the context of 5G, showcasing the ability of these technologies to navigate the complexities of modern wireless networks. Additionally, the study by Mazhar et al. (2022) delved into the role of AI and ML in managing smart energy systems and intelligent building operations, further emphasizing the broad applicability of these technologies in enhancing 5G network functionality.

These contributions collectively underscore the significant role that both innovative antenna designs and AI/ML technologies play in the advancement of 5G networks. By addressing key challenges such as frequency reconfigurability, interference mitigation, and complex decision-making processes, these research efforts pave the way for more robust, efficient, and user-friendly wireless communication systems. As the field continues to evolve, the integration of such technologies into the fabric of 5G networks will undoubtedly remain a critical area of focus, driving the development of even more sophisticated and capable wireless infrastructures in the future. Building upon this foundation, the intricate balance between enhancing system reliability, managing data traffic, and optimizing spectral and energy efficiencies becomes paramount. The utilization of advanced mathematical techniques, such as the Richardson and Neumann series expansion, exemplifies the innovative approaches adopted to streamline operations like matrix inversion, which is crucial for minimizing latency in network communications. This backdrop sets the stage for a detailed examination of channel estimation strategies, which are central to the optimization of massive MIMO systems. The exploration of various methodologies, including Maximum Likelihood, Minimum Mean Square Error (MMSE), and Zero-Forcing (ZF) algorithms, as seen in references (Björnson et al., 2017; Ali et al., 2023; Arshad et al., 2020; Yang and Marzetta, 2013; Asif et al., 2022), highlights the concerted efforts to refine channel estimation processes. Among these, the MMSE estimator stands out for its adeptness at balancing computational efficiency with the ability to mitigate interference effectively, thereby enhancing SE in the complex, user-dense environments characteristic of 5G networks. The advancements in EE and SE within massive MIMO systems underscore the evolving nature of 5G technology. While circuit power preference algorithms have sought to maximize EE, the development of precoding techniques has had a more significant impact on SE, especially in MIMO systems. Notably, antenna selection schemes aim to enhance the EE of UL transmissions despite the increased power consumption by mobile antennas, as explored in references (Arshad et al., 2020; Thakur and Mishra, 2019). Additionally, pilot reuse techniques emerge as a practical solution for reducing co-channel interference without expanding bandwidth, offering a nuanced approach to managing cell density. These strategies, alongside the exploration of low-complexity channel estimation methods such as MMSE, Element-wise MMSE, and LS estimators, navigate the trade-offs between computational efficiency and SE. The discussions around power consumption and EE at the base stations further accentuate the importance of efficient DL MIMO systems, incorporating zero-forcing, beamforming, and optimal channel strategies to improve network performance (Al-Mogren, 2008). Furthermore, the exploration of Full-duplex (FD) models appropriate for short-range communications, like WiFi and small-cell networks, highlights the pursuit of reduced transmitted power without compromising system integrity, as evidenced in research (Nguyen et al., 2020). The technological advancements in antenna technology, signal processing, and energy management form the cornerstone of efforts to refine 5G networks, setting the stage for the advent of 6G technologies (Almelah and Hamdi, 2016; Ahmed et al., 2021; Asif et al., 2021; Hassan et al., 2022).

As the telecommunication industry begins its forward-looking journey from 5G towards 6G, the anticipation surrounding the capabilities and potential of 6G networks is palpable within the research community. The integration of emerging technologies such as fog and cloud computing with the Internet of Things (IoT) is seen as a cornerstone for these future networks, aiming to provide enhanced services across various sectors, including healthcare. Similarly, the research by Shafiei et al. (2021) tackled the complex multiobjective optimization problems (MOOPs) that emerge at the intersection of 5G and 6G technologies, emphasizing the role of advanced algorithms in navigating these challenges. These efforts underscore a collective ambition to transcend the limitations of current wireless systems, striving for a future where 6G networks facilitate unprecedented levels of connectivity, efficiency, and service delivery. Reflecting on the body of work dedicated to massive MIMO research reveals a rich tapestry of innovation and inquiry, spanning the foundational principles of the technology to the cutting-edge advancements that promise to redefine the landscape of wireless communication. The depth and breadth of these studies highlight not only the technical challenges inherent in developing and deploying massive MIMO systems but also the interdisciplinary efforts required to address them. From antenna design and optimization to the nuanced application of AI and ML in network management, the research community continues to push the boundaries of what is technically feasible. This pursuit not only aims to enhance the capabilities of existing 5G networks but also sets the stage for the advent of 6G technologies. In doing so, it reflects a broader ambition within the field of wireless communication: to continuously evolve in anticipation of future demands, ensuring that emerging networks are not only more powerful and efficient but also more adaptable and user-centric than their predecessors.

## 2.2. Gap in current research

While the advancements in massive MIMO systems for 5G and beyond have been significant, there remains a discernible gap in the research, particularly in the context of seamless integration and optimization of these systems within multi-cell environments. The challenges associated with ensuring consistent and efficient performance across diverse and dynamically changing network conditions have not been fully addressed. This gap is especially pronounced in the areas of inter-cell interference management, adaptive channel estimation techniques, and the scalability of precoding and decoding strategies to accommodate the exponential increase in data demands and user connectivity.

One of the primary areas where this gap manifests is in the optimization of network resources to achieve a balance between SE and EE without compromising the Quality of Service (QoS) in densely populated areas. Current research efforts have made strides in individual aspects of massive MIMO technology, such as enhancing antenna design or improving channel estimation methods. However, there is a need for a holistic approach that encompasses not just the technical specifications of the massive MIMO systems but also their operational efficiency in real-world scenarios. Moreover, the integration of emerging technologies such as machine learning and artificial intelligence in the optimization of massive MIMO systems presents a promising avenue that has yet to be fully explored. While there have been preliminary studies in this direction, the potential for AI and ML algorithms to dynamically adapt and optimize network parameters in real time based on changing environmental conditions and user demands is a research area ripe for exploration. Furthermore, the transition from 5G to 6G networks introduces new dimensions to the existing challenges, with the expectation of even higher data rates, lower latency, and the incorporation of technologies like IoT and edge computing. This transition underscores the necessity for innovative solutions that can seamlessly integrate massive MIMO systems into the fabric of future wireless networks, ensuring that they are not only capable of meeting the current demands but are also future-proof. In addressing these gaps, the proposed research aims to develop adaptive and intelligent frameworks for Dense (Massive) MIMO systems that are capable of self-optimization in multi-cell environments. By leveraging the power of AI and ML, alongside novel antenna technologies and advanced signal processing techniques, the goal is to create a new paradigm for massive MIMO systems that can dynamically adjust to the demands of the network and its users, ensuring optimal performance and efficiency.

This exploration into the untapped potential of massive MIMO systems seeks to bridge the current gap in research, paving the way for next-generation wireless networks that are more robust, efficient, and capable of accommodating the exponential growth in global connectivity and data consumption.

## 3. Modeling of UL and DL in dense (Massive) MIMO systems

This section delves into the architecture of a multi-cell Dense (Massive) MIMO setup, focusing on the intricacies of models for the transmission of UL and DL streams, the application of linear processing strategies, and the underlying channel models. It specifically outlines the dynamics of UL and DL MIMO transmissions within and between cells j and l, as depicted in Fig. 1. The channel vectors $h_{lk}^{j}$ and $h_{jk}^{l}$ are examined for UL and DL transmissions, respectively, linking base station BS j to user equipment UE k. For UL transmissions, the signal model incorporates the intended signal alongside inter-cell interference and noise components. Conversely, the DL transmission signal model includes an additional component representing the intra-cell signal.

Based on these preliminary considerations, the subsequent segments further elaborate on the modeled system.

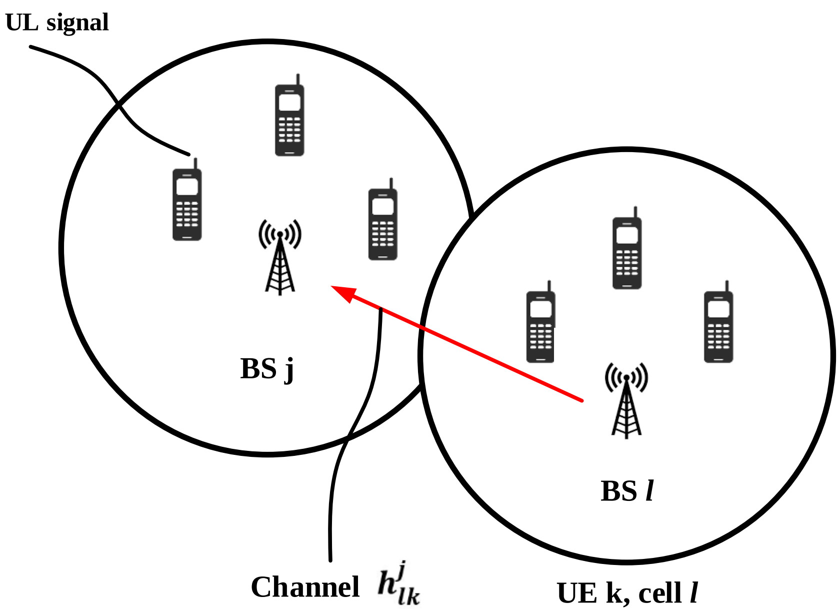


**Fig. 1:** UL transmission in cell j and cell l

### 3.1. UL

In the UL transmission, a user defined as "K" initiates the process by transmitting data to the correspondence BSs, which have a symbol vector in the "$l$" cell is $s_l = [s_{l,1} \quad s_{l,2} \ldots \ldots \ldots s_{l,k}]$. $y_j^{UL} \epsilon\, \mathbb{C}^M$ donates as received $UL$ signal by correspondence users "K" at $BSj$ becomes:

$$y_j^{UL} = \sqrt{\rho ul} \sum_{l=1}^{L} \sum_{K=1}^{K_i} h_{lk}^{j} S_{lk}^{UL} + n_j^{UL} \tag{1}$$

In Eq.1, the $n_j^{UL}$ is considered as an additive receiver noise which is further described as "$n_j^{UL} \sim \mathcal{CN}\left(O_{M_j}, \sigma_{UL}^2 I_{M_j}\right)$," while $O_{M_j}$ defines as zero mean value with $\sigma_{UL}^2$ as a variance. In cell "$l$," *the* $UL$ transmission is "$s_{lk}^{UL} \epsilon\, \mathbb{C}$" whereas the power is "$p_{UL,lk} = \mathbb{E}\{|s_{lk}^{UL}|^2\}$." It is considered as $\rho_{UL} > 0$ for the UL SNR. Now $UL$ signal $y_j^{UL} \epsilon\, \mathbb{C}^M$ becomes:

$$y_j^{UL} = \sqrt{\rho_{UL}} \sum_{K=1}^{K_j} h_{jk}^{j} S_{jk}^{UL} + \sqrt{\rho_{UL}} \sum_{\substack{l=1 \\ i \neq j}}^{L} \sum_{K=1}^{K_i} h_{li}^{j} S_{li}^{UL} + n_j^{UL} \tag{2}$$

The desired signal is $\sqrt{\rho_{UL}} \sum_{K=1}^{K_j} h_{jk}^{j} S_{jk}^{UL}$ whereas inter-cell interference is $\sqrt{\rho_{UL}} \sum_{\substack{l=1 \\ i \neq j}}^{L} \sum_{K=1}^{K_i} h_{li}^{j} S_{li}^{UL}$. The BS in cell "j" selects the corresponding receive combining vector defined as $y_j^{UL} \epsilon\, \mathbb{C}^M$ for separating the desired UE signal and it is written as:

$$V_{jk}^{UL} y_j^{UL} = \sqrt{\rho_{UL}}\, V_{jk}^{UL} h_{jk}^{j} S_{ji}^{UL} + \sqrt{\rho_{UL}} \sum_{\substack{i=1 \\ i \neq k}}^{K_j} V_{jk}^{UL} h_{jk}^{j} S_{ji}^{UL} + \sqrt{\rho_{UL}} \sum_{\substack{i=1 \\ i \neq j}}^{L} \sum_{i=1}^{K_i} V_{jk}^{UL} h_{jk}^{j} S_{ji}^{UL} + n_j^{UL} \tag{3}$$

where, the desired signal is $\sqrt{\rho_{UL}}\, V_{jk}^{UL} h_{jk}^{j} S_{ji}^{UL}$ and the rest of the terms are intra-cell signals and inter-cell interference.

### 3.2. DL

This section outlines the DL transmission as shown in Fig. 2, where a BS "$j$" transmits the following signal in the cell "$l$":

$$x_l = \sum_{i=l}^{k_l} W_{lir_{li}} \tag{4}$$

where, $w_{lr} \in C^{M_l}$ defined as a transmit precoding vector. The received signal $y_j^{DL} \epsilon\, \mathbb{C}$ can be considered as:

$$y_j^{DL} = \sqrt{\rho_{DL}} \sum_{l=1}^{L} (h_j^{DL})^H xl + n_j^{DL} \tag{5}$$

The DL symbol vector is $x_l = [x_{l,1} \quad x_{l,2} \dots \dots \dots x_{l,k}]$ by considering "$n_j^{DL}$" as an additive receiver noise. $\sqrt{\rho_{DL}} > 0$ is used for the SNR same as for UL. Then DL signal $y_j^{DL}$ is:

$$y_j^{DL} = \sqrt{\rho_{DL}} \sum_{l=1}^{L} \sum_{i=1}^{K_l} (h_{jk}^{DL})^H W_{lirli} + n_j^{DL} \tag{7}$$

$$y_j^{dl} = \sqrt{\rho_{DL}} \quad (h_{jk}^j)^H w_{jkr_{jk}} + \sqrt{\rho_{DL}} \sum_{\substack{i=1 \\ i \neq k}}^{K_j} (h_{jk}^j)^H W_{jir_{ji}} + \sqrt{\rho_{DL}} \sum_{\substack{l=1 \\ l \neq j}}^{L} \sum_{i=1}^{K_l} (h_{jk}^{DL})^H W_{lir_{li}} + n_j^{DL} \tag{8}$$

where, the desired signal is $\sqrt{\rho_{DL}} \; (h_{jk}^j)^H w_{jkr_{jk}}$ and the rest of the terms are intra-cell signals and inter-cell interference.

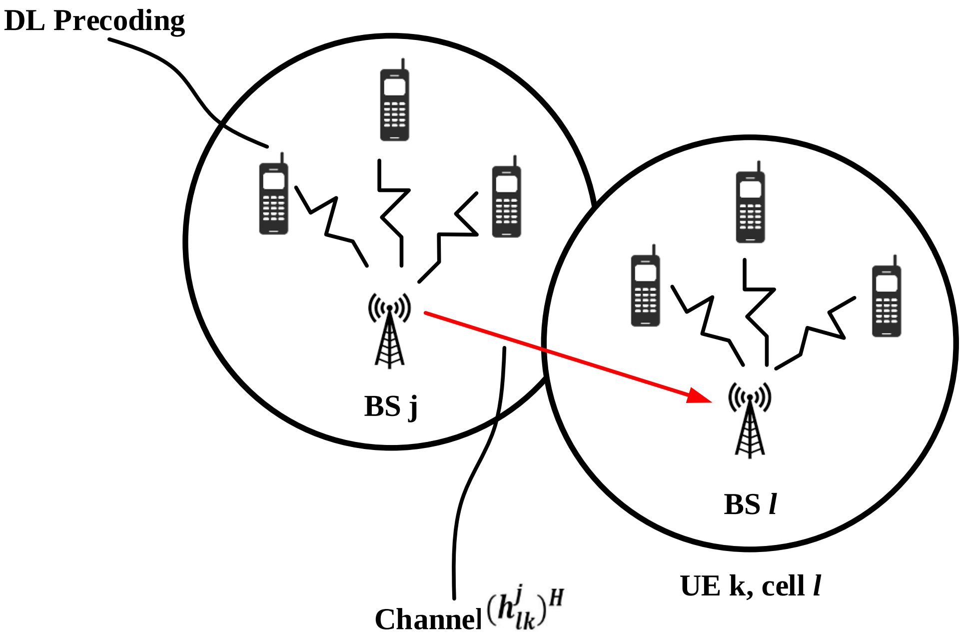


**Fig. 2:** DL transmission in cell j and cell l

## 4. Methodology and analytical framework

This section outlines the analytical framework and methodologies employed to investigate the SE of UL and DL transmissions within a multi-cell massive MIMO setup. An initial evaluation of different channel estimators sets the stage for our analysis, focusing on the channel estimation capabilities of MMSE, Element-Wise MMSE (EW-MMSE), and LS. Despite the computational simplicity of LS and EW-MMSE, their associated loss in SE is considerable, making MMSE the preferred choice due to its superior SE despite its higher computational complexity (Asif et al., 2022). Following the selection of the MMSE channel estimator, we proceed to examine various combining and precoding schemes through the application of proposed numerical equations to assess the SE of UL and DL transmissions.

The computational workflow of our model is depicted in Fig. 3, beginning with UL data and the calculations of the channel estimation. Subsequent steps involve the application of various combining and precoding schemes using the same vectors, culminating in the optimization of the average sum of SE for each cell. This iterative process continues until the computation of SE is maximized.

### 4.1. Estimation for the channel

In the dedicated UL scenario, each cell transmits a pilot sequence, enabling BSs to calculate their own local channel $(H_{jj})$, assuming mutual orthogonality of the sequence. To estimate the channel vector $(\hat{h}_{li}^j)$, expressed as:

$$y_{jk}^{tr} = \hat{h}_{UL}^j + \sum_{l \neq j} \hat{h}_{ULi}^j + \frac{1}{\sqrt{\rho tr}} n_{jk} \tag{8}$$

and

$$\hat{h}_{ULi}^j = \sqrt{p_{ULi}} R_{ULi}^j \Psi_{ULi}^j Y_{jULi}^p \tag{9}$$

where, $Y_{jUL}^p$ is the UL pilot transmission, and the pilot sequence is:

$$\Psi_{ULi}^j = \left(\sum_{(v,i') \in p_{UL}} pvi'^{\tau_r} R_{ULl'i'}^j + \sigma_{ULi}^2 I_{M_j}\right)^{-1} \tag{10}$$

The estimation error $\hat{h}_{ULi}^j = h_{ULi}^j - \hat{h}_{ULi}^j$ has correlation matrix $C_{ULi}^j = \mathbb{E}\{\hat{h}_{ULi}^j (\hat{h}_{ULi}^j)^H\}$ indicating:

$$C_{ULi}^j = R_{ULi}^j - p_{ULi} R_{ULi}^j \Psi_{ULi}^j R_{ULi}^j \tag{11}$$

The MMSE estimation leverages the orthogonal property to ensure that the estimated error remains statistically independent from $\hat{h}_{UL}^{j}$. In scenarios where user equipments (UEs) transmit using identical pilot sequences, the potential for mutual contamination of channel estimations exists. Despite the statistical independence of the channels, such interference can degrade estimation quality by elevating the Mean Squared Error (MSE) and rendering the channel estimates statistically interdependent. However, this form of channel estimation is capable of diminishing the impact of interference caused by UEs utilizing the same pilot sequence. Massive MIMO systems, distinguished from traditional networks by their capacity to support a vast number of UEs with shared pilot sequences, are particularly adept at mitigating this interference. Furthermore, the MMSE estimator is designed to reduce the MSE of channel estimates significantly, as described by the following formula:

$$\mathbb{E}\left\{\left\|\mathrm{h}_{ULi}^{j}-\hat{\mathrm{h}}_{ULi}^{j}\right\|^{2}\right\}=\mathbb{E}\left\{\left\|\hat{\mathrm{h}}_{ULi}^{j}\right\|^{2}\right\}=\mathbb{E}\left\{\mathrm{tr}\left(\hat{\mathrm{h}}_{ULi}^{j}\left(\hat{\mathrm{h}}_{ULi}^{j}\right)^{u}\right)\right\}=\mathrm{tr}\left(C_{ULi}^{j}\right) \tag{12}$$

We consider the cell $j$ and cell $l$ for the $UE$ $k$ and $ULi$ the correlation matrix at BS j is:

$$\mathbb{E}\left\{\hat{\mathrm{h}}_{jk}^{j}\left(\hat{\mathrm{h}}_{ULi}^{j}\right)^{u}\right\}=\begin{cases}\sqrt{p_{ULi}P_{jk}}R_{jk}^{j}\Psi_{ULi}^{j}R_{ULi}^{j} & (UL,i)\in\mathcal{P}_{jk}\\ O_{M_j\times M_j} & (UL,i)\notin\mathcal{P}_{jk}\end{cases} \tag{13}$$

where, the antenna correlation coefficient is:

$$\frac{\mathbb{E}\left\{\left(\mathrm{h}_{ULi}^{j}\right)^{u}\mathrm{h}_{ULi}^{j}\right\}}{\sqrt{\mathbb{E}\left\{\left\|\mathrm{h}_{jk}^{j}\right\|^{2}\right\}\mathbb{E}\left\{\left\|\mathrm{h}_{ULi}^{j}\right\|^{2}\right\}}}=\begin{cases}\dfrac{\mathrm{tr}\left(R_{ULi}^{j}R_{jk}^{j}\Psi_{ULi}^{j}\right)}{\sqrt{\mathrm{tr}\left(R_{jk}^{j}R_{jk}^{j}\Psi_{ULi}^{j}\right)\mathrm{tr}\left(R_{ULi}^{j}R_{ULi}^{j}\Psi_{ULi}^{j}\right)}} & (UL,i)\in\mathcal{P}_{jk}\\ 0 & (UL,i)\notin\mathcal{P}_{jk}\end{cases} \tag{14}$$

Here $\mathbb{E}\left\{\left(\mathrm{h}_{li}^{j}\right)^{u}\mathrm{h}_{li}^{j}\right\}=0$ for all UEs with $(UL,i)\neq(j,k)$. The non-zero expectation is determined from the UL transmission, considering all $(UL,i)\in\mathcal{P}_{jk}$, whereas the channel vector is $y_{jk}^{p}=y_{jULi}^{p}$, written as $\mathbb{E}\{y_{jULi}^{p}(y_{jULi}^{p})^{u}\}=\tau_p\left(\Psi_{ULi}^{j}\right)^{-1}$ and the normalized MSE (NMSE) is written as:

$$\mathrm{NMSE}_{UL}^{j}=\frac{\mathrm{tr}\left(C_{UL}^{j}\right)}{\mathrm{tr}\left(R_{UL}^{j}\right)} \tag{15}$$

The MMSE approach to channel estimation is utilized to compare the quality of various estimation schemes across different scenarios. This estimation technique provides ample statistical data for UL data transmission, aiding in the decoding process. However, such computations require the inversion of the matrix $\Psi_{ULi}^{j}$, which adds complexity to the process, especially when dealing with a large number of antennas and users (Van Chien et al., 2018). This complexity necessitates a more straightforward calculation method, leading to the implementation of EW-MMSE. Lemma 1 provides estimates for both error and error-free vectors. It operates under the assumption that the correlation matrix $R_{ULIi}^{j}$ relies on the diagonal elements of $A_{ULi}^{j}|_{mm}$.

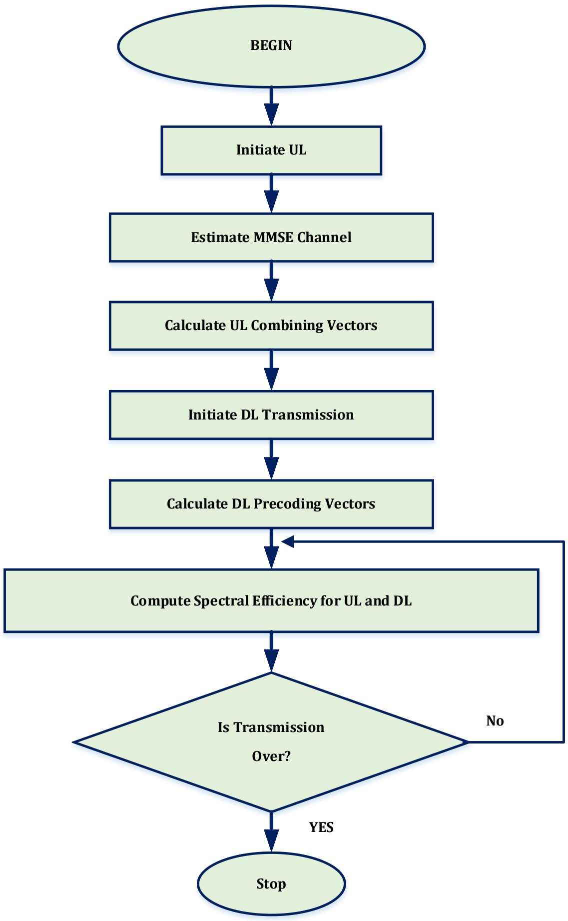


**Fig. 3:** Computational flow of the proposed model

**Lemma 1:** When base station l employs an EW-MMSE approach for estimating the channel between user k within cell l, it is possible to estimate each channel component using the standard MMSE method. However, EW-MMSE goes beyond this by providing estimates for both the vectors with error and those without, effectively capturing a comprehensive picture of the channel's state.

$$A_{ULi}^{j}|_{mm}=\frac{\sqrt{p_{ULi}}|R_{ULIi}^{j}|_{mm}}{\sum_{(l',i')\epsilon p_{li}}p_{UL'i'}\tau_p|R_{l'i'}^{j}|_{mm}+\sigma_{UL}^{2}}\quad m=1,\ldots\ldots..M \tag{16}$$

The computational process EW-MMSE is notably more straightforward than that for the traditional MMSE, except when it comes to diagonal spatial correlation matrices, which require individual estimation of each channel element. It's worth mentioning that the EW-MMSE is advantageous as it simplifies the complexity through $A_{ULi}^{j}$, streamlining the estimation process:

$$\mathrm{MSE}=\mathrm{tr}\left(R_{ULi}^{j}\right)-\sum_{m-1}^{M}\frac{p_{ULi}\tau_p(|R_{ULi}^{j}|_{mm})^{2}}{\sum_{(UL',i')\epsilon p_{ULi}}p_{UL'i'}\tau_p|R_{UL'i'}^{j}|_{mm}+\sigma_{UL}^{2}} \tag{17}$$

An LS channel estimator is known as a simple estimator. It is not considered a noise in the calculation ultimately, it overcomes the complexity (Ngo et al., 2013). For this channel estimator, Lemma 2 is.

**Lemma 2:** As the desired channel is $\sqrt{p_{ULi}}\tau_{pi}\hat{h}^{j}_{ULi}$ in cell $l$ and $\hat{h}^{j}_{ULi}$is an LS estimator. In this regard, the MSE deviation becomes:

$$\left\|y^{pi}_{jULi} - \sqrt{p_{ULi}}\tau_{pi}\hat{h}^{j}_{ULi}\right\|^{2}, \hat{h}^{j}_{ULi}$$

where,

$$\hat{h}^{j}_{li} = \frac{1}{\sqrt{p_{ULi}}\tau_{pi}} y^{pi}_{jULi} \tag{18}$$

This term $\mathbf{A}^{j}_{ULi} = \frac{1}{\sqrt{p_{ULi}}\tau_{pi}}\mathbf{I}_{M_j}$ is known for LS estimator where $Mj$ defines as a proportional to the complexity. The MSE becomes:

$$\mathrm{MSE} = \mathrm{tr}\left(\sum_{(UL',i')\in\frac{p_{iULi}}{UL,i}} \frac{p_{UL'i'}}{p_{ULi}}\boldsymbol{R}^{j}_{UL'i'} + \frac{\sigma^2_{UL}}{p_{ULi}\tau_{pi}}\mathbf{I}_{M_j}\right) \tag{19}$$

### 4.2. SE for UL with MMSE estimator

As per discussed in previous section, the $BSj$ receives a signal $y^{ul}_{j} \epsilon\, \mathbb{C}^{M}$ by considering the power $p_{ul,lk} = \mathbb{E}\left\{\left|s^{ul}_{lk}\right|^{2}\right\}$ then UL capacity forms as:

$$\mathrm{V}^{\mathrm{UL}}_{jk}\mathrm{y}_j = \mathrm{V}^{\mathrm{UL}}_{jk}\hat{\mathrm{h}}^{j}_{jk}\mathrm{s}_k + \mathrm{V}^{\mathrm{H}}_{jk}\tilde{\mathrm{h}}^{j}_{jk}\mathrm{s}_{jk} + \sum_{\substack{i=1\\ i\neq k}}^{K_j}\mathrm{V}^{\mathrm{H}}_{jk}\mathrm{h}^{j}_{ji}\,\mathrm{s}_{jk}\sum_{\substack{l=1\\ i\neq j}}^{L}\sum_{i=1}^{K_1}\mathrm{V}^{\mathrm{UL}}_{jk}\mathrm{h}^{j}_{Uli}\,\mathrm{s}_{li} + \mathrm{V}^{\mathrm{UL}}_{jk}\mathrm{n}_j \tag{20}$$

$$\mathrm{SE}^{UL}_{jk} = \frac{\tau_{ul}}{\tau_{coh}}\mathbb{E}\{\log_2(1+\mathrm{SINR}^{\mathrm{L}}_{jk})\} \tag{21}$$

$\frac{\tau_{ul}}{\tau_{coh}}$ is a pre-log factor.

The effective SNR can be written as:

$$\mathrm{SINR}^{\mathrm{UL}}_{jk} = \frac{p_{jk}\left|\mathrm{v}^{\mathrm{H}}_{jk}\hat{\mathrm{h}}^{j}_{jk}\right|^{2}}{\sum_{l=1}^{L}\sum^{K_1}_{\substack{i=1\\(UL,i)\neq(j,k)}} p_{Uli}\left|\mathrm{v}^{\mathrm{H}}_{jk}\hat{\mathrm{h}}^{j}_{jk}\right|^{2} + \mathrm{v}^{\mathrm{H}}_{jk}\left(\sum_{l=1}^{L}\sum_{ULi=1}^{K_1}p_{Uli}\mathbf{C}^{j}_{Uli} + \sigma^2_{UL}\mathbf{I}_{M_j}\right)\mathrm{v}_{jk}} \tag{22}$$

As per $\mathrm{SINR}^{\mathrm{UL}}_{jk}$ used in (21), UE is optimized through M-MMSE combining vector for $k = 1, \dots, K_j$ and $\mathbf{V}^{\mathrm{ULM-MMSE}}_{jk} = [\mathrm{v}_{j1} \dots \mathrm{v}_j\mathrm{k}_j]$ which is formulated as:

$$\mathbf{V}^{\mathrm{ULM-MMSE}}_{jk} = \mathrm{tr} * p_{jk}\left[\sum_{l=1}^{L}\sum_{i=1}^{K_1}p_{Uli}\left(\hat{\mathrm{h}}^{j}_{Uli}\left(\hat{\mathrm{h}}^{j}_{Uli}\right)^{u} + \mathbf{C}^{j}_{Uli}\right) + \sigma^2_{UL}\mathbf{I}_{M_j}\right]^{-1}\hat{\mathrm{h}}^{j}_{jk} \tag{23}$$

leading to

$$\mathrm{SINR}^{\mathrm{ULM-MMSE}}_{jk} = \mathrm{tr} * p_{jk}\left(\hat{\mathrm{h}}^{j}_{Uli}\right)^{u}\left[\sum_{l=1}^{L}\sum^{K_1}_{\substack{i=1\\(l,i)\neq(j,k)}} p_{Uli}\,\hat{\mathrm{h}}^{j}_{Uli}\left(\hat{\mathrm{h}}^{j}_{Uli}\right)^{u} + \sum_{l=1}^{L}\sum_{i=1}^{K_1}p_{Uli}\mathbf{C}^{j}_{Uli} + \sigma^2_{UL}\mathbf{I}_{M_j}\right]^{-1}\hat{\mathrm{h}}^{j}_{jk} \tag{24}$$

In situations where the estimated channels are already known, the process not only enhances the SINR but also reduces the MSE. It is worth noting that the formula given in expression of Eq. 24 accurately optimizes SINR specifically for massive MIMO systems. As previously mentioned, while a reduction in computational complexity may lead to a decrease in SE, MMSE is recognized for its superior performance in maintaining high SE. Accordingly, the various combining strategies for the MMSE channel estimator, as introduced earlier, are detailed in Table 1, which includes computations for combining vector multiplications. A thorough analysis of SE is presented in Section 5.

### 4.3. SE of DL

As indicated by Eq. 7, the expression of the signal received $y^{DL}_{jk}$ for DL in cell $l$ becomes:

$$y^{DL}_{jk} = \underbrace{E\{\sqrt{\rho_{DL}}(h^{DL}_{jk})^{H}W^{DL}_{jk}\}r^{DL}_{jk}}+\underbrace{\sqrt{\rho_{DL}}\left((h^{DL}_{jk})^{H}W^{DL}_{jk} - E\{(h^{DL}_{jk})^{H}W^{DL}_{jk}\}r^{DL}_{jk}\right)}+\underbrace{\sqrt{\rho_{DL}}\sum_{\substack{i=1\\ i\neq k}}^{K_j}(h^{DL}_{jk})^{H}W^{DL}_{ji}r^{DL}_{ji}} + \underbrace{\sqrt{\rho_{DL}}\sum_{\substack{l=1\\ l\neq j}}^{L}\sum_{i=1}^{K_l}(h^{l}_{jk})^{H}W_{DLi}r_{DLi}}+\underbrace{n_{jk}} \tag{25}$$

**Table 1:** The computational complexity/coherence block across various combining schemes

| Scheme name | Multiplication factor for reception | Computation of vectors |
|---|---|---|
| Multi-cell- minimum means squared error | $\tau_{\mathrm{UL}}\mathrm{M_j}\mathrm{K_j}$ | $\sum_{l=1}^{L}\frac{(3\mathrm{M_j^2}+\mathrm{M_j})\mathrm{K_l}}{2}+\frac{\mathrm{M_j^3}-\mathrm{M_j}}{3}+\mathrm{M_j}\tau_{\mathrm{p}}(\tau_{\mathrm{p}}-\mathrm{K_j})$ |
| Single-cell - minimum means squared error | $\tau_{\mathrm{UL}}\mathrm{M_j}\mathrm{K_j}$ | $\frac{3\mathrm{M_j^2}\mathrm{K_j}}{2}+\frac{\mathrm{M_j}\mathrm{K_j}}{2}+\frac{\mathrm{M_j^3}-\mathrm{M_j}}{3}$ |
| Regularized zero forcing | $\tau_{\mathrm{UL}}\mathrm{M_j}\mathrm{K_j}$ | $\frac{3\mathrm{K_j^2}\mathrm{M_j}}{2}+\frac{3\mathrm{K_j}\mathrm{M_j}}{2}+\frac{\mathrm{K_j^3}-\mathrm{K_j}}{3}$ |
| Zero forcing | $\tau_{\mathrm{UL}}\mathrm{M_j}\mathrm{K_j}$ | $\frac{3\mathrm{K_j^2}\mathrm{M_j}}{2}+\frac{\mathrm{K_j}\mathrm{M_j}}{2}+\frac{\mathrm{K_j^3}-\mathrm{K_j}}{3}$ |
| Maximum ratio | $\tau_{\mathrm{UL}}\mathrm{M_j}\mathrm{K_j}$ | ------- |

The desired signal can be represented by the expected value $E\{\sqrt{\rho_{DL}}(h^{DL}_{jk})^{H}W^{DL}_{jk}\}r^{DL}_{jk}$, where $r^{DL}_{jk}$ is the pre-coded data signal and the average pre-coded channel is expressed as $E\{(h^{DL}_{jk})^{H}W^{DL}_{jk}\}$. This formulation includes terms for intra-cell as well as inter-cell interference, with the third and fourth terms corresponding to each, respectively. Additionally, the second term reflects the desired signal in the presence of unknown channel conditions. The selection of transmit precoding vectors, with respect to SE, relies on the concept of hardening bounding, which is applicable across various types of precoding vectors and channel estimations. For user equipment k in cell j, the DL channel capacity, in terms of SE, can be characterized by a lower bound:

$$\underline{SE}_{jk}^{DL} = \frac{\tau_{DL}}{\tau_{coh}} log_2\left(1 + \underline{SINR}_{jk}^{DL}\right) \text{ bit/Hz} \tag{26}$$

where, $\frac{\tau_{DL}}{\tau_{coh}} presents$ a ratio of samples of DL data and samples for each coherent block. $\underline{SINR}_{jk}^{DL}$ becomes:

$$\underline{SINR}_{jk}^{DL} = \frac{\rho_{jk}|E\{W_{jk}^{H}h_{jk}^{DL}\}|^2}{\sum_{l=1}^{L}\sum_{i=1}^{K_l}\rho_{DLi}E\left\{|W_{DLi}^{H}h_{jk}^{l}|^2\right\}-\rho_{jk}|E\left\{W_{jk}^{H}h_{jk}^{DL}\right\}|^2+\sigma_{DL}^2} \tag{27}$$

In prior studies such as those referenced in Ngo et al. (2013) and Chen et al. (2013), energy consumption models were primarily focused on radiated power and did not account for the power consumption of the radio frequency (RF) circuitry. Although these models have shown some enhancements in massive MIMO systems, they were largely based on theoretical analyses. For instance, the optimization of EE through power allocation and time division has been examined by Asif et al. (2021), while the trade-offs between SE and EE have been explored by Ngo et al. (2013). There is an emerging requirement for cellular system designs in massive MIMO to re-evaluate EE performance based on practical, real-world measurements. For example, research has been conducted on the number of antennas, UE density, and power consumption models to optimize EE, considering both UL and DL transmissions in multiuser massive MIMO networks. A practical power consumption model, as introduced by Xin et al. (2015), has been adopted for the current analysis. We have scrutinized several system parameters, as indicated in Table 2, which include propositions on the number of antenna estimations, evaluations of maximum user capacity, and modeling of effective transmit power alongside circuit power.

**Table 2:** Simulation parameters for the proposed model

| No. | Items | Values |
|---|---|---|
| 1 | No. of antenna | $M = 500$ |
| 2 | Circuit power | $CP_l = 15\,Watt$ |
| 3 | Effective transmit power | $ETP = 2\,Watt$ |
| 4 | $\frac{\sigma^2}{\beta_0^0}$ | -3dBm |
| 5 | μ | 0.5 |

For $W_{jk} = \frac{\hat{h}_{jk}^{DL}}{\sqrt{E\{t\|\hat{h}_{jk}^{DL}\|^2\}}}$, $\underline{SINR}_{jk}^{DL}$ considered as MR precoding based on the same channel estimation used in UL and calculated as:

$$\underline{SINR}_{jk}^{DL} = \frac{\rho_{jk}^{DL}tr\left(R_{jk}^{DL}\Psi_{jk}^{DL}R_{jk}^{jDL}\right)p_{jk}^{DL}}{\underbrace{\sum_{l=1}^{L}\sum_{i=1}^{K_l}\frac{\rho_{DLi}tr\left(R_{lk}^{l}\Psi_{lk}^{l}R_{lk}^{l}\right)}{tr\left(R_{lk}^{l}\Psi_{lk}^{l}R_{lk}^{l}\right)}}+\underbrace{\sum_{(l,i)\epsilon p_{jk}\backslash(j,k)}\frac{\rho_{DLi}p_{jk}\tau p\left(R_{jk}^{l}\Psi_{lk}^{l}R_{lk}^{l}\right)}{tr\left(R_{lk}^{l}\Psi_{lk}^{l}R_{lk}^{l}\right)}}+\sigma_{DL}^2} \tag{28}$$

where, $\Psi_{jk}^{DL}\Psi_{li}^{DL}$ defined in Eqs. 9 and 10 for UL, which are non-coherent interference and coherent interference. $R_{li}^{j} = \beta_{li}^{j}I_{M_j}$is a spatially uncorrelated factor. The same combing vectors $\mathbf{V}_{jk}^{\text{ULM-MMSE}} = [\mathrm{v}_{j1} \ldots \mathrm{v}_j\mathrm{k}_j]$ are used in these precoding schemes for DL.

$$\mathbf{V}_{jk}^{\text{DLM-MMSE}} = [\mathrm{v}_{j1} \ldots \mathrm{v}_j\mathrm{k}_j] = \begin{cases} V_{JK}^{M-MMSE} & of\ \ M-MMSE\ precoding \\ V_{JK}^{S-MMSE} & of\ S-MMSE\ precoding \\ V_{jk}^{RZF} & of\ RZF\ precoding \\ V_{JK}^{ZF} & of\ \ ZF\ precoding \\ V_{JK}^{MR} & of\ \ MR\ precoding \end{cases} \tag{29}$$

## 5. Results and discussion

The expressions for SE in both UL and DL transmissions, as derived in the preceding sections, are subjected to simulation and verification within a specified massive MIMO cellular network framework. The assessment of SE employs various combining and precoding schemes, including S-MMSE, M-MMSE, ZF, RZF, and MR, all of which utilize 'M' number of antennas as outlined by the simulation parameters detailed in Table 3.

**Table 3:** Simulation parameters for combining and precoding schemes

| Simulation Parameter | Values. |
|---|---|
| Bandwidth | B= 20MHz |
| Coherence time | $T_{Coh}$ =10ms |
| Maximum distance/radius of cell | 200 meters |
| Attenuation of a channel | $\omega = 10^{-3.5}$ |
| $UE_s$ | K= 18 |
| Effective signal to noise ratio | (−10 to 20) dB |
| Noise power on receiver side | −94dBm |
| No. of samples/coherence block | $\tau_{coh} = 200$ |

### 5.1. Results comparison of channel estimators

The realization of the maximum capabilities of massive MIMO systems is contingent upon choosing the most effective channel estimation method during UL pilot transmission. In the scenario we propose, base station j estimates the channel for user equipment k, while other cells may concurrently transmit identical pilot signals. The effective SNR is considered across a range from -10dB to 20dB, as illustrated in Table 3. Figs. 4 and 5 present the outcomes related to the number of complex multiplications required and the performance of MMSE in comparison to the number of antennas in a multi-cell environment, utilizing EW-MMSE, MMSE, and LS channel estimators. We note that these estimators have been numerically analyzed in Section A of the methodology, with specific considerations for EW-MMSE and LS as outlined in Lemma 1 and Lemma 2, respectively. As identified by Asif et al. (2022), the MMSE channel estimator yields superior SE compared to its counterparts, albeit with increased computational complexity. The statistical results derived from the MMSE estimator are robust, indicating that the MSE diminishes progressively as the effective SNR increases, a trend confirmed by the results in Fig. 5. This observation aligns with our channel estimation models and corroborates the patterns reported in Asif et al. (2022). Despite this, our model prioritizes SE and aims to minimize MSE without overly concerning itself with complexity. Consequently, the findings showcased in Fig. 5 suggest that our model can achieve improved SE, which allows us to set aside the complexity considerations highlighted in Fig. 4, given the intricate nature of the MMSE estimator.

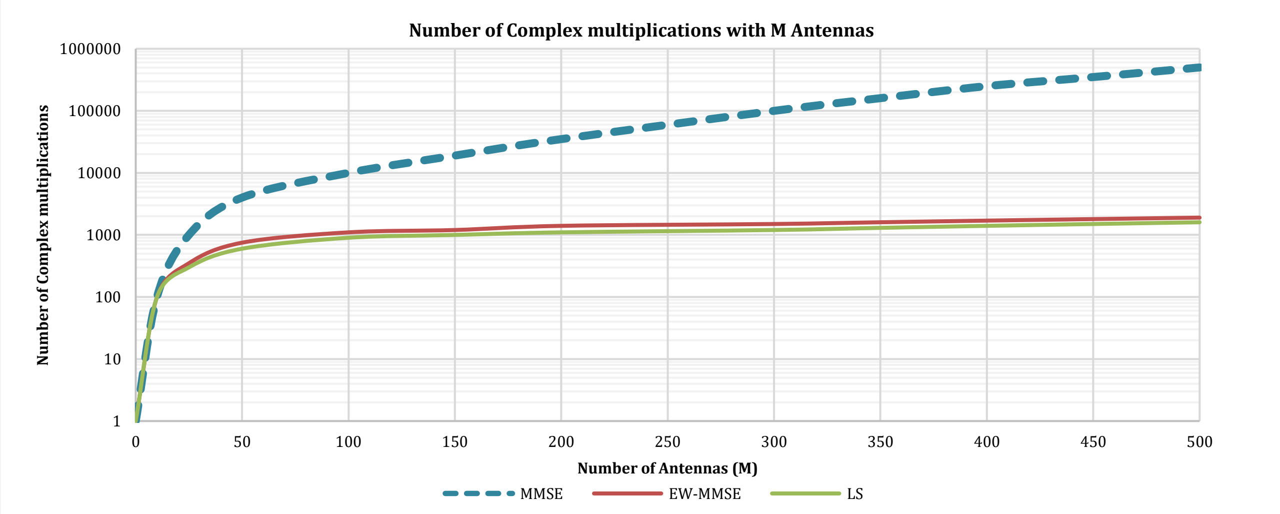


**Fig. 4:** Results for the number of complex multiplication vs M

### 5.2. Results comparison of SE in different UL combining schemes

Fig. 6 illustrates the SE outcomes for various combining strategies. The proposed model shows a notable enhancement in SE over the work presented by Tan et al. (2018). SE within the system sees a steady rise with an increase in the number of antennas and cells. This is exemplified by the performance of M-MMSE, which outstrips S-MMSE in terms of SE, with SE gains amplifying as more antennas are introduced. The scholarly consensus underscores the pivotal role of channel estimation in uplifting the SE of UL massive MIMO systems, rather than focusing solely on combining schemes. Moreover, the results from our proposed model are straightforwardly contrasted with the MMSE combining scheme detailed in Ozdogan et al. (2018), following an extensive numerical evaluation of channel estimation. A comparative summary showcasing the advancements in SE relative to prior work is tabulated, where our implemented MMSE estimator for multi-cell M-MMSE exhibits significant progress in SE, surpassing the combining schemes and M-MMSE outlined in Ozdogan et al. (2018).

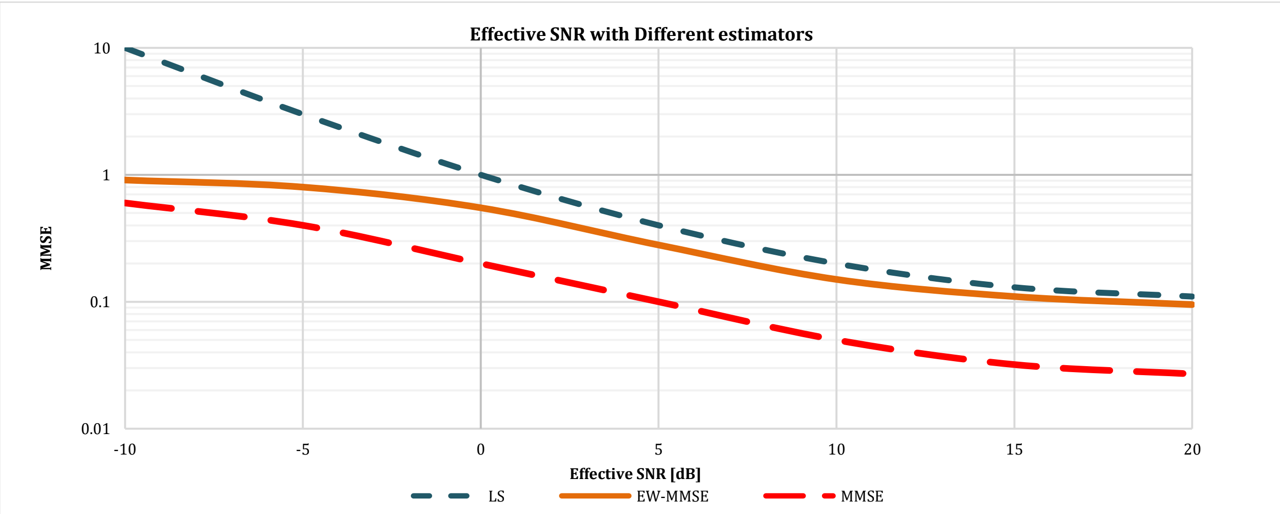


**Fig. 5:** Results of MMSE vs M

### 5.3. Results comparison of SE in different DL precoding schemes

Fig. 7 displays the calculated average sum of SE per cell in a massive MIMO system context, utilizing five different precoding strategies. Based on the number of users (K) and the effective SNR outlined in Table 2, it is evident that the average SE per cell escalates with an increase in the number of antennas. This underlines the substantial advantages of deploying large antenna arrays at base stations. It was also noted that, given the same system configuration, the average SE rate achieved with MMSE precoding is approximately twice that of the MR scheme. A review of previous research, as summarized in Table 4, consistently indicates that the MMSE precoding strategy outperforms other techniques, making it the preferred choice for massive MIMO systems. In assessing the performance of our proposed massive MIMO system's precoder relative to alternative approaches, as depicted in Fig. 7, we find that the simulation results for M-MMSE are in line with findings from Tan et al. (2018) and Li et al. (2015). The RZF matches with Li et al. (2015) and Nguyen et al. (2020), the RF corresponds with Van Chien et al. (2018) and Chen et al. (2013), and the MR is consistent with Van Chien et al. (2018), Ngo et al. (2013), Chen et al. (2013), Xin et al. (2015), Ozdogan et al. (2018), Tan et al. (2018), and Li et al. (2015), as detailed in Table 4. Both the numerical formulations and the simulation outcomes demonstrate that the average sum of SE per cell has experienced an uptick when juxtaposed with prior studies Tan et al. (2018), Li et al. (2015), and Nguyen et al. (2020), validating the effectiveness of the proposed numerical expressions. The results obtained from our proposed models substantiate the potential of massive MIMO systems to significantly boost SE within 5G cellular networks. Our models delineate the architecture for both UL and DL communications, showcasing the UL SE when employing the MMSE estimator in contrast with both EW-MMSE and LS estimators. Subsequently, the maximum-ratio (MR) precoding scheme is employed to enhance the DL SE, a consideration that recent studies, such as Chen et al. (2013), have not incorporated.

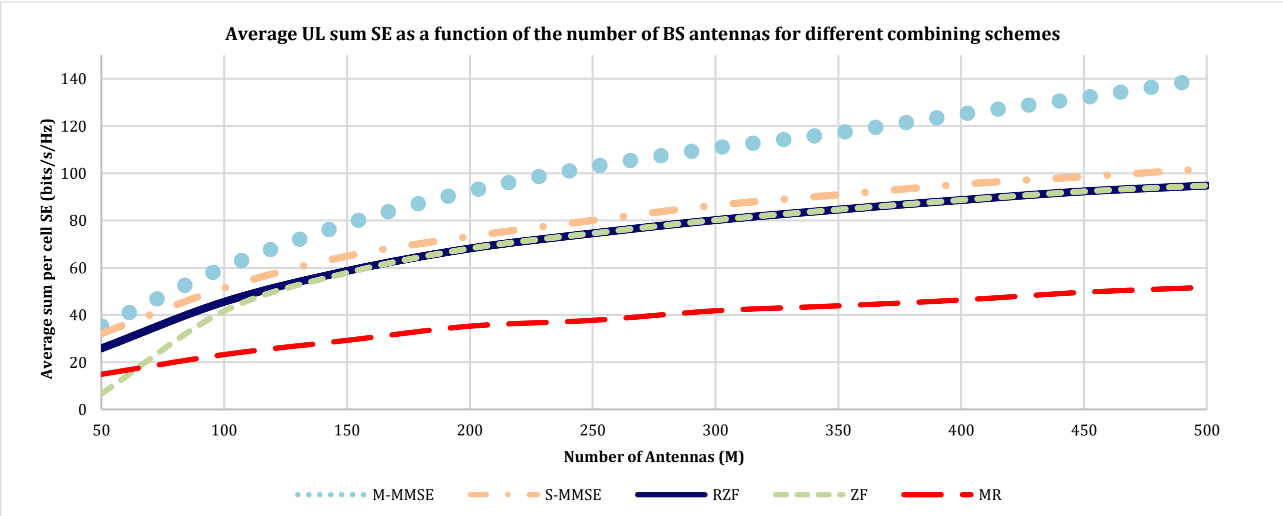


**Fig. 6:** Results of Desired SE for different combining schemes in UL transmission

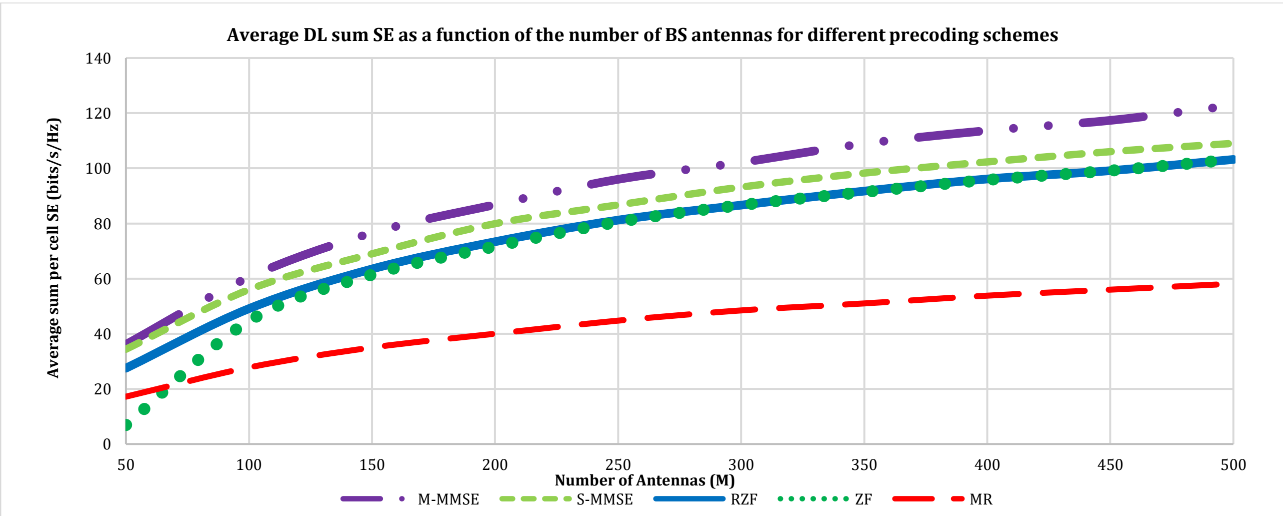


**Fig. 7:** Results of desired SE for different precoding schemes in DL transmission

**Table 4:** Comparison results of EE and M with Tan et al. (2018), Li et al. (2015), and Nguyen et al. (2020) vs proposed model

| Combining schemes | M-MMSE | | S-MMSE | | RZF | | RF | | MR | |
|---|---|---|---|---|---|---|---|---|---|---|
| | EE | M | EE | M | EE | M | EE | M | EE | M |
| Ozdogan et al. (2018) | 33 | 100 | ----- | ----- | ----- | ----- | ----- | ----- | ----- | ----- |
| Proposed model | 140 | 500 | 105 | 500 | 90 | 500 | 90 | 500 | 52 | 500 |
| **Precoding schemes** | | | | | | | | | | |
| Tan et al. (2018) | 105 | 500 | ----- | 500 | ----- | 500 | 103 | 500 | 58 | 500 |
| Li et al. (2015) | 110 | 500 | ----- | 500 | 108 | 500 | ----- | 500 | 45 | 500 |
| Nguyen et al. (2020) | ----- | 128 | ----- | 128 | 110 | 128 | 110 | 128 | 85 | 128 |
| Proposed model | 125 | 500 | 110 | 500 | 105 | 500 | 105 | 500 | 65 | 500 |

It has been observed that SE escalates with the expansion in the number of antennas and cells, with M-MMSE exhibiting higher SE compared to S-MMSE, particularly as the antenna count increases. Unlike the findings of Tan et al. (2018), which focused solely on M-MMSE, our investigation extends to a variety of combining schemes, including S-MMSE, M-MMSE, RF, RZF, and MR. Moreover, our model incorporates up to 500 antennas, acknowledging that while this may elevate power consumption, the substantial antenna array contributes to a relatively higher EE, as detailed in Table 4.

The discussion also recognizes the necessity for practical system designs in massive MIMO cellular systems, where EE performance is critically evaluated through real-world measurements. Previous works referenced in Tan et al. (2018), Li et al. (2015), and Nguyen et al. (2020) have limited their energy consumption models to only considering radiated power, omitting the power consumption of RF circuits. Therefore, our work adopts a practical power consumption model as outlined in Chen et al. (2013) to perform a comprehensive analysis. This includes an examination of the number of antennas, the capacity for maximum user support, and the modeling of both the practical effective transmit power and circuit power.

## 6. Conclusion

In our investigation, we have successfully enhanced the SE per cell within a massive MIMO system framework, utilizing MMSE channel estimation alongside various combining and precoding strategies. Initially, a multi-cellular scenario was conceptualized to derive expressions for both UL and DL transmissions, subsequently leading to the development of a realistic, efficient, and applicable model. The MMSE channel estimator was selected over EW-MMSE and LS due to its superior capability to elevate the reachable average sum of SE per cell, as corroborated by the schemes mentioned above. Simulation outcomes have underscored the significant advancements facilitated by our approach.

Our research foundation was laid on MMSE channel estimation, which, despite its computational complexity, emerged as a superior estimator in bolstering SE per cell compared to the EW-MMSE and LS alternatives. Monte Carlo simulations conducted in MATLAB affirmed the efficacy of MMSE in combining and precoding approaches. While MMSE stood out as the optimal channel estimator, it's noteworthy that the MR scheme was recognized for its simplicity. Despite the intricate calculations associated with MMSE, its implementation is justified by the marginal variance in outcomes against the substantial SE enhancements it delivers. Testing of combining and precoding schemes with the proposed numerical models revealed that M-MMSE is the most effective strategy for addressing SE concerns. MR precoding, although not as effective, offers a less complex solution capable of functioning amidst intercell interference with simpler channel estimation computations. In conclusion, the findings of this study indicate that optimizing channel estimation is pivotal for advancing SE in both UL and DL transmissions.

Looking ahead, the prospects for advancing massive MIMO systems are substantial. Future research can expand upon the current work by exploring alternative channel estimation techniques that balance computational load and efficiency. There is also an opportunity to delve into adaptive algorithms that could dynamically adjust combining and precoding schemes in real time based on changing network conditions. Moreover, as 5G technology evolves and the industry moves toward 6G, the role of massive MIMO systems in supporting increased device density and data throughput will undoubtedly become more significant. Addressing the challenges of scalability and interoperability with emerging technologies such as IoT and edge computing will be essential. As the research involved in optimized selection of antennas and devices to make better use of energy and improve how much information can be sent over frequencies higher than 6 GHz. Since massive MIMO works well in these high frequencies, there's still a lot of room to make energy use and information sending even better, which is why more research is needed. Lastly, practical implementations and field testing of the proposed models will be critical for validating theoretical findings and ensuring that the massive MIMO systems can meet the demands of real-world applications.

## Compliance with ethical standards

### Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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