Performance Analysis of Constrained AP Selection in Distributed MIMO Networks

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Contents

Abstract

As the demand for reliable wireless networks continues to grow, there is an increasing need for innovative network architecture concepts to meet the escalating requirements for high throughput and good coverage. One such solution is Distributed Massive Multiple-Input Multiple-Output (MIMO), a technology that leverages a network of spatially distributed Access Points (APs) to serve User Equipments (UEs) simultaneously. This architecture offers significant advantages in terms of coverage, serving capacity, and Spectral Efficiency (SE) (a measure of how effectively the network uses its available bandwidth) by utilizing spatial diversity, where signals are transmitted and received from multiple locations. However, while Distributed Massive MIMO holds great promise, it faces scalability challenges, particularly as the number of UEs increases and the number of available APs is limited. To tackle this challenge, AP selection becomes a critical strategy. Instead of all APs in the network, a subset of APs is selected to serve a given User Equipment (UE). This selective approach not only reduces computational complexity but also optimizes the use of network resources (i.e., available APs), making the system more practical and scalable. However, as UE density increases while the number of available APs remains fixed, the need for smart AP selection becomes crucial. In scalable distributed MIMO, each UE desires to be served by an optimal set of APs with the best channel conditions. Yet, as the number of UEs increases, each AP must serve more UEs, which introduces two significant challenges. First, the risk of pilot contamination rises, a phenomenon where UEs sharing the same pilots cause inter-UE interference, leading to a degradation in overall network performance. Second, the increased signaling and data processing required as each AP serves more UEs results in higher computational costs. Adequate AP selection is essential in mitigating these challenges by balancing performance with cost. This thesis focuses on the problem of constrained AP selection, specifically examining how to optimize AP selection when resources like the number of APs and pilots are limited. Our research introduces and evaluates various AP selection methods, including a novel approach we designed and refer to as the "Fair AP Request" method. This method is designed to enhance network performance by reallocating underutilized AP resources to the weakest UEs, thereby ensuring a more efficient distribution of network serving capacity. Our analysis reveals that the Fair AP Request method not only achieves near-peak spectral efficiency but does so with a relatively low algorithmic complexity. This makes it a robust and scalable solution for distributed massive MIMO networks, particularly in resource-constrained scenarios. The findings of this thesis provide valuable insights into the design and optimization of future wireless networks, highlighting the importance of AP selection in maximizing network efficiency and scalability.

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INTRODUCTION

The exponential growth in demand for high data rates and reliable wireless communication, fueled by the proliferation of smart devices and the increasing dependence on wireless networks for everyday applications, has made network architectural design a critical focus in recent years. To meet these escalating demands, recent discussions have centered on optimizing network architecture to achieve significant improvements in spectral efficiency - how efficiently the network utilizes its available bandwidth - and system capacity, which determines the number of UEs the network can support [1].

Traditional cellular networks have long been the backbone of mobile communication, utilizing centralized Base Stations (BSs) to connect users within specific geographic cells. While this architecture was effective in earlier generations of mobile networks, it is increasingly inadequate in addressing modern demands. As the number of connected devices surges and data consumption continues to grow, these networks face critical challenges such as capacity limits, poor coverage, and severe interference, particularly at the edges of cells where users are far away from the Base Station (BS) and therefore typically experience the lowest service quality [2].

To mitigate these issues, the field of wireless communication has evolved towards Massive MIMO technology. Massive MIMO involves deploying large antenna arrays at both the transmitting BS and receiving user devices, enabling the network to transmit multiple data streams simultaneously over the same frequency band - a process known as spatial multiplexing. This approach significantly enhances spectral efficiency, allowing the network to accommodate more users at higher data rates. As a result, Massive MIMO offers substantial improvements in coverage and capacity, addressing some of the key limitations of traditional cellular networks [1].

However, despite these advancements, the centralized nature of Massive MIMO, where large antenna arrays are installed at a single BS, still presents challenges. In densely populated urban environments or areas with complex geographical features, the placement of these base stations can lead to suboptimal performance. Users located far from the BS or in obstructed areas may experience degraded signal quality, and the network may suffer from imbalances in load distribution. Additionally, as user densities increase, particularly with the proliferation of Internet of Things (IoT) devices, centralized networks struggle to scale their infrastructure to meet demand without incurring significant costs [3].

Distributed Massive MIMO networks offer a revolutionary shift in wireless communication by decentralizing antenna arrays and dispersing numerous APs across the coverage area. This approach addresses the limitations of traditional centralized architectures by enabling each UE to be served by multiple APs, chosen based on the best available channel conditions. This not only optimizes connection quality but also improves overall network performance. Additionally, Distributed Massive MIMO eliminates traditional cell boundaries, which often cause reduced data rates and increased inter-cell interference at cell edges, ensuring consistent, high-quality service across the entire coverage area [4].

While Distributed Massive MIMO transforms wireless communication by addressing many limitations of traditional networks, it also introduces challenges, especially in resource-constrained environments. As demand for higher data rates and more reliable connections grows, Distributed Massive MIMO systems struggle in scenarios with limited APs and high UE densities. Serving all UEs with all APs simultaneously is impractical and inefficient, leading to resource contention and increased interference [5].

This issue has driven the development of Scalable Distributed Massive MIMO, where only a subset of APs serves each UE based on channel conditions, optimizing spectral efficiency. However, as UE density increases while the number of available APs remains fixed, the need for smart AP selection becomes critical. When the number of UEs grows, each AP must serve more UEs, leading to two significant challenges. First, the limited number of available pilots increases the risk of pilot contamination, where UEs sharing pilots cause inter-UE interference, degrading overall performance. Second, the increased signaling and data processing required as each AP serves more UEs results in higher computational costs. Adequate AP selection is essential in mitigating these challenges, particularly in high-density environments, by balancing performance with cost. This ensures that Distributed Massive MIMO remains scalable and capable of meeting the growing demands of modern wireless networks [6].

This thesis focuses on constrained AP selection in scalable Distributed Massive MIMO networks, a critical area of research that addresses these challenges. We explore how to optimize AP selection under the constraints of limited APs and pilots to ensure that the network remains scalable, efficient, and capable of meeting the demands of modern networks. Through our research, we aim to develop strategies that not only enhance the performance of scalable Distributed Massive MIMO networks but also ensure their practical applicability in real-world scenarios where resources are often limited.

This thesis aims to address constrained AP selection in scalable Distributed Massive MIMO networks. The primary objectives are as follows:

- To demonstrate the importance of AP selection methods.
- To understand the constraints of network design and its effects on AP selection.

- To design a new AP selection method during this research and evaluate its performance.
- To analyze and compare the performance of the new and existing AP selection methods against the ideal scenario and a traditional cellular scenario.
- To assess the system cost associated with each AP selection method, balancing performance gains against computational complexity and resource usage.
- To examine the impact of different network conditions, such as user density and pilot sequence length, on the performance of AP selection methods.

The scope of this thesis encompasses the theoretical analysis, simulation, and performance evaluation of AP selection methods in distributed Massive MIMO networks. The key contributions of this work include:

- A comprehensive review of existing AP selection methods and their limitations.
- The development and validation of a new AP selection method designed by us to enhance performance under specific network conditions.
- A detailed comparative analysis of the proposed and existing methods using extensive simulations.
- Demonstrating the performance superiority of our method "Fair AP Request" over most dominant existing AP selection methods.
- Considering realistic constraints, such as a limited number of APs and a maximum number of UEs each AP can serve.
- Insights into the trade-offs between performance and system cost, providing guidelines for the practical deployment of distributed Massive MIMO networks.

Ultimately, by addressing the challenges associated with constrained AP selection in Distributed Massive MIMO networks, this thesis aims to contribute to the development of more efficient and especially scalable wireless communication systems.
The thesis is structured as follows:

Chapter 2: Background - This chapter provides an overview of the fundamentals of wireless networks design, Massive MIMO technology, and distributed Massive MIMO networks. Key concepts such as channel estimation, pilot contamination, and AP selection are also discussed.

Chapter 3: System Model - This chapter details the network model, channel model, and evaluation metrics used in the study. It also outlines the assumptions and constraints considered in the analysis.

Chapter 4: AP Selection Methods - This chapter describes the different AP selection methods evaluated in this study, including existing methods and the new method proposed in this research.

Chapter 5: Results - This chapter presents the results of the performance evaluation, including comparative performance analysis and computational cost assessment under various network conditions.

Chapter 6: Conclusion and Future Work - The final chapter summarizes the key findings, discusses their implications for network design, and suggests directions for future research.

2

BACKGROUND

In this chapter, we look at the foundational aspects of wireless networks, tracing the evolution of network architectures and highlighting key concepts essential for understanding scalable Distributed Massive MIMO networks. Section 2.1 addresses the fundamentals of wireless networks, emphasizing the significance of designing efficient network architectures to meet the ever-increasing demands for data rates, reliability, and coverage. We will explore the modern challenges that current networks face, such as spectrum efficiency, energy consumption, and scalability. Section 2.2 takes us through the evolution of network architectures. This section starts with the traditional cellular networks and progresses to the introduction of massive MIMO technology, which significantly enhances network capacity and efficiency. We then discuss the transition to Distributed MIMO, highlighting its benefits over the centralized approaches. Finally, we move towards scalable Distributed MIMO, which aims to address the challenges of high user densities and maintain optimal network performance. Section 2.3 focuses on the key concepts in scalable distributed massive MIMO networks. Here, we cover the constraints on network design, discussing the need for efficient AP selection to minimize resource wastage and enhance network performance. We also delve into channel estimation techniques essential for maintaining reliable communication and examine the issue of pilot contamination, a significant challenge in massive MIMO systems. Lastly, Section 2.4 provides a literature review, offering a comprehensive overview of existing research and advancements in the field of distributed massive MIMO networks. This review sets the stage for understanding the current state of the art and identifying areas for future research.

2.1 FUNDAMENTALS OF WIRELESS NETWORKS

Understanding the basics of wireless networks will be necessary to understand complex questions and innovations as Massive MIMO and Distributed Massive MIMO. This section provides an overview of key concepts and challenges in wireless network design for a deeper comprehension of modern network architectures and their evolution.

Firstly, we begin by discussing the importance of network architecture design and how the strategic arrangement of network components can significantly impact performance, scalability, and efficiency. This includes addressing the large requirements and cost constraints that drive the development of new and improved network structures.

Secondly, we take a look at the modern challenges that wireless networks face. These challenges include the increasing demand for higher data rates, reliable connectivity, and the ability to efficiently manage a vast number of devices in diverse and dynamic scenarios. By understanding these challenges, we can understand the necessity for innovative solutions and the continuous evolution of network technologies and architectures.

Overall, this section establishes a foundation for understanding the essential factors that affect wireless network performance, providing context for the upcoming discussions on the progression of network architectures and the technologies designed to tackle these fundamental issues.

2.1.1 Network Architecture Design

The design of network architecture forms the backbone of any wireless communication system, influencing its performance, scalability, and reliability. As wireless networks continue to evolve, accommodating an ever-increasing number of connected devices and supporting a variety of services with different QoS requirements, the importance of an optimized network architecture has never been more critical. A well-designed network architecture ensures efficient use of resources, minimizes latency, enhances coverage, and improves the overall user experience. Conversely, a poorly designed architecture can lead to bottlenecks, inefficient resource utilization, and degraded performance, ultimately undermining the potential of the network [2].

Over the years, significant research has been dedicated to developing network architectures that can meet the growing demands of modern communication systems. Traditional cellular networks, which rely on a hierarchical structure of base stations and cells, have served as the foundation for mobile communications. However, as user density and data traffic have exploded, these conventional architectures have encountered limitations in terms of scalability and efficiency. This has prompted the exploration of more advanced architectures, such as massive MIMO and distributed MIMO systems, which offer enhanced spectral efficiency, improved energy efficiency, and the ability to serve a large number of users simultaneously [3].

The shift towards more modern network architectures is driven by the need to support emerging applications, such as IoT, augmented reality, and autonomous vehicles, all of which require reliable, low-latency communication. In this context, designing a network architecture that can flexibly adapt to varying conditions and efficiently manage resources is essential. The architecture must not only handle the current traffic demands, but also be scalable to accommodate future growth in the number of users and the diversity of services [3].

One key aspect of network architecture design is the distribution of processing and decision-making capabilities. Centralized architectures, while simpler to manage, often struggle with latency and scalability issues as the network grows. On the other hand, distributed architectures, where processing is spread across multiple nodes, can offer significant advantages in terms of flexibility and robustness. However, these architectures also introduce challenges, such as increased complexity in coordination and the need for algorithms to manage distributed resources effectively [7].

In addition to these technical considerations, the design of network architecture must also take into account economic factors, such as the cost of deployment and maintenance. A well architecture network strikes a balance between performance and cost, ensuring that the network can deliver high-quality service without becoming prohibitively expensive to operate [3].

Overall, the design of network architecture is a critical component in the development of modern wireless communication systems. It requires a careful balance of technical innovation, practical constraints, and future-proofing to ensure that the network can meet the demands of today while being prepared for the challenges of tomorrow. As we continue to push the boundaries of wireless technology, the role of network architecture design will only become more important, driving the need for ongoing research and development in this field.

In Section 2.2 we will take a closer, more detailed look at the advances done in the field of network architecture design.

2.1.2 Modern Challenges

As wireless communication networks continue to evolve, they face increasingly complex challenges that could significantly reduce their performance and ability to meet growing demands. The exponential rise in connected devices, driven by advancements such as the IoT, 5G, and the upcoming 6G technology, has created an unprecedented strain on network infrastructure. This strain is found in several critical areas, each posing unique challenges to the sustainability and scalability of modern networks [8].

One of the biggest challenges is scalability. As networks expand to support a larger number of users and devices, they must be able to scale efficiently without a corresponding increase in complexity or cost. Traditional network architectures, which often rely on centralized management and fixed infrastructure, struggle to scale effectively as demand grows. This scalability issue is particularly acute in environments where the number of connected devices is expected to grow exponentially, such as in smart cities or industrial deployments. The need for a network architecture that can efficiently scale to meet these demands without sacrificing performance or increasing operational complexity is more pressing than ever [6].

In addition, resource allocation in modern networks has also become a significant challenge. In a network with a high density of devices and APs, efficiently allocating resources such as bandwidth and power becomes increasingly complex. Traditional resource allocation strategies, which were designed for less dense and more centralized networks, may no longer be sufficient to manage the demands of modern communication systems. As networks become more distributed and devices become more numerous, new approaches to resource allocation are needed to ensure that all devices can access the resources they need without causing congestion or overloading any part of the network [6].

Furthermore, networks operating in challenging and constrained conditions such as in industrial environments face unique challenges that further complicate network design and performance. These environments often feature limited space for installing infrastructure, leading to constraints on the number and placement of APs. The presence of heavy machinery, dense materials, and complex layouts can also create significant obstacles for signal propagation, leading to increased interference and reduced coverage. Furthermore, the high concentration of devices, particularly with the integration of IoT in industrial settings, intensify the strain on network resources and increases the potential for interference. Addressing these challenges requires innovative solutions that can operate effectively within the constraints of industrial environments while maintaining high levels of performance and reliability [9].

2.2 EVOLUTION OF NETWORK ARCHITECTURES

In this section, we explore the development of network architectures from traditional cellular networks to scalable distributed Massive MIMO systems. We begin by examining the transition from conventional cellular structures to Massive MIMO, highlighting the advancements in the performance. Next, we discuss the shift towards distributed MIMO, focusing on how decentralizing the antenna arrays enhances coverage and network resilience. Finally, we transition to the concept of scalable distributed Massive MIMO, illustrating how it addresses the limitations of previous architectures and how it is able to meet the increasing demands of modern wireless communication. This section provides a comprehensive overview of the technological advancements and designs that have shaped our wireless networks.

2.2.1 From Cellular to Massive MIMO

The evolution of wireless network architectures has been marked by transformative innovations aimed at meeting the escalating demand for higher data rates, enhanced spectral efficiency, and improved reliability. Traditional cellular networks, which rely on dividing geographic areas into cells, have long been the foundation of mobile communication. In these networks, each cell is served by a single BS that manages communication with all the UEs within its coverage area. However, as the number of UEs and the demand for data have surged, the limitations of cellular networks have become increasingly apparent, particularly in terms of spectral efficiency and interference management [10].

Massive MIMO technology was introduced as a revolutionary approach to overcome these challenges. By equipping BSs with a large number of antennas, Massive MIMO enables the simultaneous transmission of multiple data streams to different UEs, significantly boosting spectral efficiency. This is achieved through spatial multiplexing, allowing the system to serve many UEs on the same time-frequency resources by leveraging the spatial dimension [10].

Despite these advantages, the implementation of Massive MIMO in cellular networks has limitations. The centralized nature of traditional cellular architectures means that each UE is primarily served by the nearest BS, which can result in suboptimal performance in terms of load balancing and coverage, especially in dense urban environments. This limitation has led to exploring more distributed network architectures, paving the way for the next phase in wireless network evolution: Distributed MIMO [6].

2.2.2 *Transition to Distributed MIMO*

The transition from traditional cellular networks to Distributed MIMO represents a transformative shift in wireless network design, one that is driven by the increasing demands for higher data rates, improved coverage, and more robust network performance. In traditional cellular networks, each UE is typically served by a single BS, which manages all communications within a defined coverage area or cell. This architecture, while effective for many years, has inherent limitations, particularly as the number of connected devices continues to surge and the demand for data-intensive applications grows. Even with the introduction of MIMO antennas, traditional cellular networks still faced significant challenges. The concept of cells, where each BS covers a specific geographical area, inherently created issues at the boundaries or "edges" of these cells. UEs located at cell edges often experience poorer signal quality, higher levels of interference, and reduced data rates due to their distance from the serving BS and the proximity to neighboring cells. This "cell-edge problem" became a bottleneck for achieving uniform network performance, particularly in dense urban environments where the number of UEs is high [4].

To overcome these limitations, the concept of Distributed MIMO was introduced, representing a fundamental departure from the traditional cellular paradigm. In a Distributed MIMO network, the rigid cell boundaries are effectively dissolved. Instead of each UE being served by a single BS, a large number of geographically dispersed APs work together to serve the UEs across the network. These APs are typically small, low-power units that are spread throughout the coverage area, and they communicate with each other and a Central Processing Unit (CPU) to coordinate their actions [4].

The distributed MIMO architecture transforms the entire network into a vast, cooperative antenna array, where the APs collectively act as the network's antennas. This cooperative approach allows the network to leverage spatial diversity more effectively, as signals from multiple APs can be combined to improve signal quality and reduce the impact of interference. The result is a more uniform and consistent level of service throughout the coverage area, including in regions that would have been considered cell edges in a traditional network [5].

One of the most significant advantages of Distributed MIMO is its ability to mitigate the cell-edge problem that plagues traditional cellular networks. In a distributed MIMO system, all UEs, regardless of their location within the coverage area, can be served by multiple APs simultaneously. This means that even UEs that would be located at the edge of a cell in a traditional network can receive strong, reliable signals from nearby APs, leading to better overall service quality [4].

Furthermore, distributed MIMO systems can take full advantage of the spatial diversity inherent in the radio environment. By jointly processing signals from the multiple APs, the CPU can optimize the transmission and reception strategies to exploit favorable propagation conditions, such as multipath reflections, which would typically be considered a problem in a traditional network. This joint processing capability leads to improved signal quality, reduced interference, and enhanced network capacity [4].

In a typical distributed MIMO network, the APs are connected to a CPU or a set of CPUs via high-capacity backhaul links. The CPU is responsible for coordinating the actions of the APs, including tasks such as channel estimation, signal processing, and resource allocation. This centralized coordination allows the network to operate in a highly efficient manner, as the CPU can dynamically adjust the operation of each AP based on real-time network conditions and the specific needs of each UE [6].

Figure 2.1 illustrates the architecture of a Distributed MIMO network. As shown in the figure, multiple distributed APs are connected to CPUs, and these APs jointly serve the UEs within the coverage area. The architecture is designed to be highly flexible and scalable, allowing the network to accommodate a large number of UEs while maintaining high levels of performance [6].

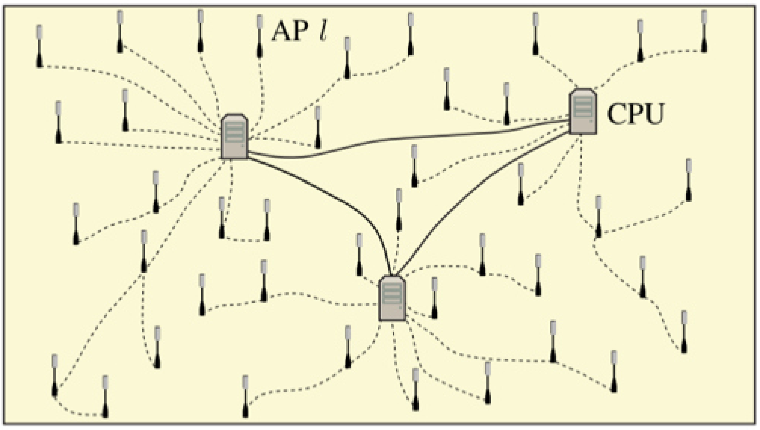


FIGURE 2.1: Illustration of a Distributed Massive MIMO network [6].

2.3 KEY CONCEPTS OF DISTRIBUTED MIMO WITH CONSTRAINED RESOURCES

In this section, we deal with the fundamental principles of scalable distributed massive MIMO networks. We begin by examining the constraints that impact network design such as resource limitations and the need for efficient AP selection methods. Next, we explore how channel estimation is done, which is crucial for maintaining high performance and reliability in these networks. We then discuss the issue of pilot contamination, which is a significant challenge in distributed massive MIMO systems, and the strategies employed to mitigate its effects. By understanding these key concepts, we can have a better overview of the crucial factors involved in developing scalable distributed massive MIMO networks.

2.3.1 Towards Scalable Distributed MIMO

As distributed MIMO networks evolve, a key challenge that arises is scalability. The fundamental idea behind distributed MIMO, deploying a large number of geographically dispersed APs to serve UEs offers significant benefits in terms of coverage, signal quality, and interference management. However, as the number of UEs increases, the system faces growing complexity, making it difficult to manage efficiently. Moreover, constraints such as limited resources (i.e. available APs) and measures to avoid pilot contamination impose hard challenges. To address these challenges, the concept of Scalable Distributed MIMO has been introduced [6].

Scalable Distributed MIMO, sometimes referred to as Cell-Free Massive MIMO in the literature, represents an advanced approach that seeks to combine the strengths of both Massive MIMO and Distributed MIMO while addressing their inherent limitations. The goal is to design a network that can scale efficiently without a corresponding increase in system complexity or overhead, ensuring that the network remains manageable and performs optimally even as it grows [6].

One of the primary innovations in Scalable Distributed MIMO is the shift from a single centralized CPU that manages the entire network to a more distributed architecture involving multiple CPUs. In a large or complex networks, managing all APs and UEs from a single CPU would not only create a bottleneck but also result in significant delays and inefficiencies. By distributing the computational load across several CPUs, each managing a subset of APs, the network can operate more efficiently, with reduced latency and improved reliability. This decentralized processing approach allows for more localized signal processing, which is crucial for maintaining high performance in the network [6].

Another critical aspect of scalability is the management of the APs serving each UE. In traditional distributed MIMO, where every AP could potentially serve every UE, the computational and signaling overhead would become overwhelming as the network scales. To mitigate this, Scalable Distributed MIMO systems limit the number of APs that serve each UE to a small, carefully selected subset. This not only reduces the burden on the network infrastructure but also optimizes the use of available resources, ensuring that the best possible channel conditions are provided to each UE without unnecessary duplication of effort. This limited serving AP set approach is crucial for scalability. By focusing the network's resources on the most effective APs for each UE, the system can maintain high levels of performance without the need for every AP to be involved in every communication. This selective service reduces the overall complexity of the network, allowing it to scale more gracefully as the number of UEs and APs increases [11].

Scalability ensures that the network can expand and adapt to changing conditions without a proportional increase in costs, complexity, or power consumption. This makes scalable distributed MIMO a critical innovation for the future of wireless communication, enabling the deployment of large-scale networks that can meet the challenges of tomorrow's connected world.

In Chapter 3, we will introduce UE-centric AP selection and in Chapter 4 we will explain the studied AP selection methods in details.

2.3.2 Constraints on Network Design

Designing wireless networks inherently involves navigating a variety of constraints that can significantly influence the overall architecture and performance. These constraints stem from factors such as physical space availability, resource limitations, and environmental conditions. In any network design, there should be a balance between providing extensive coverage, ensuring high data rates, and managing interference, all within the bounds of the available infrastructure and resources.

In much of the existing literature, it is often assumed that the number of APs in a network is much larger than the number of UEs, allowing for flexible AP selection. However, this assumption does not hold in more constrained environments, such as industrial settings, where network design faces significant challenges. In these scenarios, the physical space for deploying APs is often severely limited due to large machinery, storage areas, and complex building layouts, resulting in a much smaller number of available APs compared to the high density of UEs, such as IoT devices. Each UE seeks to be served by an optimal set of APs, but when the UE density is high, each AP is required to serve more UEs, leading to two critical challenges. First, the limited number of available pilots increases the risk of pilot contamination, where UEs sharing the same pilots cause inter-UE interference, degrading overall network performance. Second, the increased signaling and data processing required as each AP serves more UEs result in higher computational costs. These constraints make smart AP selection essential, particularly in high-density scenarios, to balance performance with resource allocation and computational costs. This need for intelligent AP selection strategies is the central focus of our work, as we aim to address these constraints, ensuring that Distributed Massive MIMO systems remain viable under these demanding conditions.

The constraints on network design, whether in general scenarios or particularly challenging environments like industrial cases, highlight the critical importance of strategic AP selection. As networks continue to evolve and face increasingly complex demands, addressing these constraints will be essential for maintaining high performance and reliability in a wide range of operational environments.

2.3.3 Channel Estimation

Channel estimation is a crucial component in the design and operation of Distributed Massive MIMO systems. The performance of these systems heavily relies on accurate knowledge of the wireless channel, as this information is used to optimize signal processing techniques such as interference management. In Distributed Massive MIMO, where numerous APs are deployed to serve UEs across a large area, the complexity and importance of channel estimation are significantly amplified [12].

In any wireless communication system, the transmitted signals undergo various forms of degradation as they propagate through the environment. These include path loss, fading, and interference, all of which must be accounted for to accurately recover the transmitted information at the receiver. In Distributed Massive MIMO systems, where the number of antennas is very large and spread across multiple locations, the variations in the wireless channel become even more complex. The ability to accurately estimate these channels is important to the system's performance, as it directly influences the effectiveness of techniques like reception across the distributed APs [13].

Channel estimation in Distributed Massive MIMO systems is typically performed using pilot signals, which are predefined sequences known to both the transmitter and the receiver. During the uplink phase, users send these pilot signals to the APs, which then estimate the channel by correlating the received signals with the known pilot sequences. This process is repeated across all APs, allowing the system to obtain a comprehensive understanding of the channel conditions between each AP-UE pair [6].

In Distributed Massive MIMO, accurate channel state information is crucial for managing interference, particularly in dense environments with a high number of users and APs. However, in high UE density scenarios, channel estimation becomes a significant burden due to the large volume of UEs and the complexity of their interactions with multiple APs. This increased demand for accurate channel estimation poses a constraint on the network due to the high signaling overhead and processing cost. To mitigate this challenge, smart AP selection becomes essential. By carefully selecting which APs serve each UE, the network can reduce the computational load associated with channel estimation, ensuring better resource allocation and enhancing overall network performance.

2.3.4 Pilot Contamination

Pilot contamination is a significant challenge in Distributed Massive MIMO systems, one that directly impacts the performance and scalability of these networks. In massive MIMO systems, the efficient estimation of the wireless channel is achieved through the use of pilot signals, that are predetermined sequences transmitted by users that allow the network to estimate the Channel State Information (CSI). However, in practical deployments, especially in large scale systems, the reuse of these pilot signals across different cells or users leads to what is known as pilot contamination. This phenomenon arises when the same pilot sequence is reused by multiple users, causing their signals to interfere with each other during the channel estimation process. The resulting interference significantly degrades the quality of the channel estimates, which in turn impacts the overall performance of the network [14].

In a massive MIMO system, channel estimation is performed using pilot sequences that are orthogonal within each cell but must be reused across different cells due to the limited number of available orthogonal sequences. When a pilot sequence is reused in different cells, the channel estimates at the base station or AP become a linear combination of the channels from all users sharing the same pilot sequence. This overlap causes interference during both the uplink and downlink phases, leading to inaccuracies in the CSI. The interference caused by pilot contamination does not diminish as the number of APs increases, making it a critical issue that limits the theoretical capacity gains promised by massive MIMO systems [10].

The impact of pilot contamination is particularly severe in Distributed Massive MIMO networks, where a limited number of APs must serve a high density of UEs. The scarcity of available pilots forces UEs to share sequences, increasing the risk of inter-UE interference and degrading overall network performance. Additionally, as more UEs connect to each AP, the signaling and data processing demands escalate, leading to higher computational costs and straining the network's resources [6]. In such high-density scenarios, smart AP selection is essential. By strategically choosing which APs serve which UEs, the network can reduce pilot contamination and balance the computational load, ensuring efficient performance while managing costs. Effective AP selection is therefore key to maintaining the balance between performance and resource constraints in Distributed Massive MIMO networks.

2.4 LITERATURE REVIEW

Traditional cellular networks face significant limitations, including capacity constraints, poor cell-edge performance, and interference management challenges. To address these, Distributed Massive MIMO systems were introduced. As discussed by Ngo et al.in [4], Cell-Free Massive MIMO eliminates cell edges by using a large number of distributed APs to jointly serve all UEs, improving spectral efficiency and user fairness. However, this approach raises new challenges, particularly around scalability and resource management. To overcome scalability issues in fully distributed Massive MIMO systems, scalable solutions with AP selection have been developed. Björnson in [6] presents a framework where only a subset of APs serves each UE, optimizing network performance while reducing complexity. This approach efficiently uses resources, particularly in dense environments, but often overlooks the complexities in highly dynamic and resource-constrained settings. In industrial settings, where network rsources are limited (i.e. available APs), robust AP selection is crucial. Aijaz in [9] highlights the challenges in these environments, such as interference from machinery and high device density, but does not focus on specific AP selection strategies. Moreover, Chen et al. in [15] introduces dynamic AP selection in 6G networks but leave gaps in AP selection under resource constraints. Despite advancements, a gap remains in studying AP selection in scenarios where the number of UEs far exceeds the limited number of APs. Existing literature, such as Ammar et al. in [11] and Interdonato et al. in [5], discuss user-centric Cell-Free Massive MIMO and scalable AP selection but do not fully address these extreme conditions. This thesis fills this gap by introducing the "Fair AP Request" method, which optimizes AP selection in constrained environments, balancing spectral efficiency and computational complexity.

3

SYSTEM MODEL

In this chapter, we introduce the framework of our study by outlining the system model that forms the basis of our analysis. We begin with the details about the network architecture in Section 3.1, where we describe the structural aspects of our network. This includes the placement and distribution of APs and UEs, along with the key design principles and assumptions that underpin our network layout. We then move to Section 3.2, where we introduce the concept of UE-centric AP selection. We discuss the motivation behind this approach, highlighting its advantages over other methods where AP selection is typically network-centric. In Section 3.3, we focus on the channel and signal models. Here, we present the mathematical formulations used to characterize the wireless channels and the signal propagation in our network. This section covers the assumptions regarding the propagation environment and the critical parameters influencing these processes. Finally, in Section 3.4, we define the evaluation metrics used to assess the performance of our network. This includes metrics for spectral efficiency. We provide detailed explanations on the calculation of these metrics and their importance in evaluating the network's performance.

3.1 NETWORK ARCHITECTURE

In this study, we consider a network architecture tailored to evaluate the performance of various AP selection methods in a distributed massive MIMO environment. The network is deployed over a designated area S, within which we position L single-antenna APs and K single-antenna UEs. This setup represents a typical dense urban or industrial scenario, where efficient and reliable communication is needed.

The distribution of UEs within the area S is modeled using a Poisson Point Process (PPP). This stochastic process captures the random nature of UE locations, simulating real-world conditions where users are unpredictably scattered across the network. The UE density is defined as $\lambda_U = K/S$, which indicates the average number of UEs per unit area. This random distribution of UEs introduces variability and complexity into the network, as each UE experiences different channel conditions based on its proximity to various APs.

On the other hand, the APs are arranged in a uniform grid pattern, ensuring an even coverage across the entire area S. The density of APs is given by $\lambda = L/S$, representing the average number of APs per unit area. This grid-based distribution of APs is designed to minimize coverage gaps and ensure that every UE has access to multiple APs, which is crucial for the implementation of the AP selection strategies analyzed in this study. The uniform placement of APs provides a consistent reference for evaluating the effectiveness of different AP selection methods, as it reduces variability in AP availability and distance, isolating the impact of the selection algorithms themselves.

We assume that both the APs and UEs remain static during the simulation. This assumption simplifies the analysis by focusing on the inherent properties of the network architecture and the AP selection algorithms without the added complexity of mobility. In a real-world scenario, this static assumption could correspond to environments like industrial settings or fixed-location IoT deployments, where the positions of UEs and APs do not change frequently.

The static nature of the APs and UEs allows us to thoroughly examine the spatial characteristics of the network and understand how the AP selection methods perform under these controlled conditions. By establishing a fixed network topology, we can focus on the intricacies of AP selection, interference management, and resource allocation, gaining deeper insights into the optimal configurations and strategies that maximize network performance.

Figure 3.1 represents the network model and gives an illustration of our network architecture. The blue cross symbols represent the APs, and the orange circles indicate the UEs.

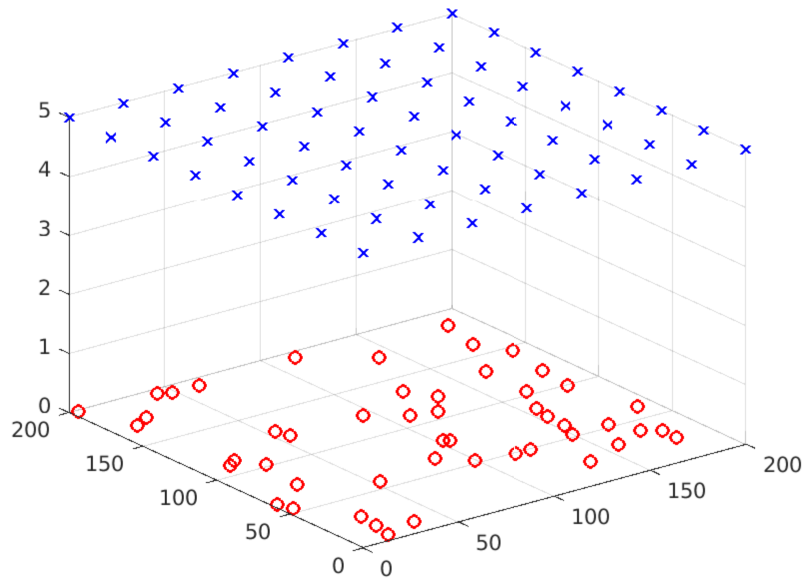


FIGURE 3.1: Network Model. The blue cross symbols represent the APs, and the orange circles indicate the UEs.

3.2 UE-CENTRIC AP SELECTION

In Distributed Massive MIMO networks, efficient AP selection is critical for optimizing network performance and user experience. Traditionally, a network-centric approach was often adopted, where APs were divided into disjoint clusters [16]. In these clusters, APs share data and CSI to serve only the UEs located within their joint coverage area. This method is very effective but inherently limited by the fixed cluster boundaries, which may not always align with the optimal coverage areas for individual UEs [16].

However, the rise of user-centric approaches has shifted the paradigm of AP selection in Distributed Massive MIMO. Instead of relying on predefined clusters, user-centric methods prioritize the individual needs and conditions of each UE. In this approach, each UE is served by a dynamic subset of APs that provides the best possible channel conditions. Unlike the network-centric method, these subsets of APs vary for each UE, making it impossible to divide the network into non-overlapping clusters [17]. Consequently, each AP must cooperate with different sets of APs when serving different UEs on the same time and frequency resources, significantly enhancing the flexibility and efficiency of the network [17]. Figure 3.2 depicts the process of UE-centric AP selection. In the figure, The black cross symbols represent the APs and the blue circles indicate the UEs. The red cross symbols represent the AP serving set of the dark blue circle UE. The serving set of APs varies for each UE in the network based on the specific conditions experienced by the UE.

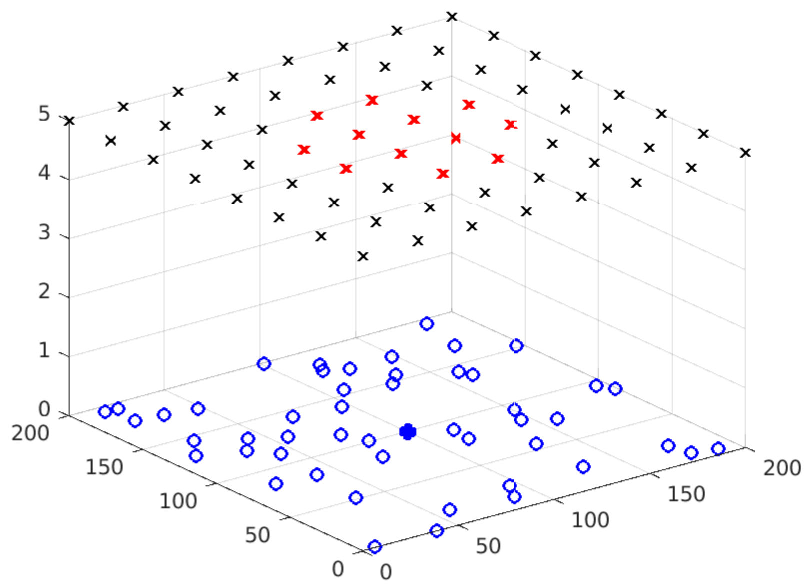


FIGURE 3.2: UE-centric AP Selection. The black cross symbols represent the APs and the blue circles indicate the UEs. The red cross symbols represent the AP serving set of the dark blue circle UE.

The concept of UE-centric AP selection emerges from the limitations of traditional cellular network architectures, where each UE is typically served by the nearest AP. This often leads to suboptimal performance due to varying channel conditions and load distribution [18]. On the contrary, UE-centric selection considers factors such as signal strength and channel quality to make more informed decisions about which APs should serve a particular UE. This approach can significantly enhance spectral efficiency, reduce latency, and improve overall network performance, especially in scenarios with varying user densities and heterogeneous service requirements [6].

The primary goals of UE-centric AP selection in Distributed Massive MIMO networks are to optimize spectral efficiency by selecting APs that provide the best channel conditions for each UE, thereby maximizing data rates and overall spectral efficiency within the network. Additionally, by distributing UEs more evenly across available APs, this approach also helps balance the network load, helps to prevent bottlenecks and ensures high performance, especially in dense deployment scenarios. Furthermore, by considering the specific needs and conditions of each UE, UE-centric AP selection enhances the reliability of the network, particularly in environments with continuously changing conditions in signal quality and interference [12].

In Chapter 4 we go into more details about the various UE-centric AP selection methods proposed and evaluated in this thesis. By comparing these methods to traditional approaches, we aim to demonstrate their advantages in terms of performance and cost in different network conditions.

3.3 CHANNEL AND SIGNAL MODELS

In this section, we take a look at the crucial aspects of channel and signal modeling, which form the backbone of our analysis of scalable distributed massive MIMO systems. Accurate channel and signal models are essential for understanding the complex interactions between the UEs and APs in the network, particularly in a dense deployment scenario where things like interference, fading, and spatial diversity play a significant role. We will introduce and discuss the specific models that capture the characteristics of the wireless environment, the propagation of signals, and the associated constraints that impact network performance. These models are designed to closely mimic real-world conditions, enabling us to draw meaningful conclusions about the performance of our various AP selection methods.

Subsection 3.3.1 begins with a detailed exploration of the channel access technique and the channel estimation used in our network model. The chosen channel access method is critical for ensuring that UEs can effectively communicate with APs, especially in a dense network environment with many users competing for limited resources. In Subsection 3.3.2, we describe the Uplink Channel Model. This model characterizes how signals transmitted from UEs are received at the APs. Subsection 3.3.3 focuses on the Downlink Channel Model, which mirrors the uplink model but with signals being transmitted from APs to UEs. The downlink channel model is crucial for understanding how the transmitted data is received by the UEs. Finally, in Subsection 3.3.4, we outline the Assumptions and Constraints that are integral to our modeling approach. We discuss the constraints imposed by the finite number of pilots available for channel estimation, the limitations on the number of UEs each AP can serve simultaneously, and the limited number of APs. These constraints play an important role in shaping the network's performance and are essential considerations in our subsequent analysis.

3.3.1 Channel Access Technique and Channel Estimation

In this subsection, we describe the channel access technique employed in our distributed massive MIMO network, which is based on Time Division Duplexing (TDD). TDD is chosen for its efficiency in massive MIMO systems, allowing for the same frequency band to be used for both uplink and downlink transmissions by separating them in time [10]. This is particularly advantageous in distributed networks, where the synchronization of CSI between multiple APs and UEs is crucial for optimal performance. The TDD communication framework we adopt is structured into discrete communication blocks, each of which has a total duration of τ_c slots. Each block is divided into two distinct phases: the pilot transmission phase and the data transmission phase. These phases are critical for ensuring accurate channel estimation and efficient data transmission. Figure 3.3 shows the structure of the TDD communication block. We see in orange the τ_p long pilot transmission phase and in blue the τ_d data transmission phase.

1. Pilot Transmission Phase: This phase occupies the first τ_p slots of each communication block. During these slots, UEs transmit known pilot sequences to the APs. The purpose of this phase is to enable the APs to estimate the uplink CSI. Since the same channel characteristics are assumed for both uplink and downlink transmissions due to channel reciprocity in TDD, the estimated CSI is also applicable for the downlink phase. The accuracy of channel estimation is pivotal for the overall system performance, as it directly influences the quality of both uplink and downlink data transmissions.

2. Data Transmission Phase: Following the pilot transmission phase, the remaining $\tau_d = \tau_c - \tau_p$ slots are dedicated to the actual data transmission. In this phase, the UEs and APs use the estimated CSI to transmit and receive data. For uplink communication, UEs send their data to the APs, while for downlink communication, APs transmit data to the UEs. The CSI obtained during the pilot phase is crucial here, as it allows the APs to pre-code signals and minimize interference, thereby enhancing the overall spectral efficiency.

An important assumption in our model is that channel estimation and signal processing are performed only once every τ_c slots, corresponding to the start of each communication block. This means that the CSI used during the data transmission phase remains constant for the entire duration of the communication block. This assumption simplifies the signal processing and reflects a realistic approach where continuous real-time channel estimation is often impractical due to computational and latency constraints.

The TDD-based channel access technique, with its distinct phases for channel estimation and data transmission, is essential for the operation of our distributed massive MIMO network. By structuring communication into these well-defined blocks, we can ensure efficient and accurate transmission of data, even in the presence of numerous UEs and APs spread across a large area. This approach not only maximizes the use of available resources but also lays the groundwork for the AP selection methods that will be analyzed in subsequent sections.

Moreover, channel estimation plays an important role in ensuring optimal system performance [6]. Accurate CSI is crucial for mitigating interference and enhancing spectral efficiency. In the uplink, APs estimate the channel coefficients for each AP-UE pair by processing the received pilot signals. This estimated information is then utilized to decode the uplink data effectively. Conversely, in the downlink, APs use the CSI to pre-code the transmitted signals, tailoring them to the specific channel conditions of each UE. As mentioned earlier, each coherence block is divided into τ_p channel uses for UL pilots and τ_d for data, with $\tau_c = \tau_p + \tau_d$. The channel between AP l and UE k is denoted by $\mathbf{h}_{kl} \in \mathbb{C}^N$, and the aggregated channel from all APs is represented as $\mathbf{h}_k = \left[\mathbf{h}_{k1}^{\mathrm{T}}, \ldots, \mathbf{h}_{kL}^{\mathrm{T}}\right]^{\mathrm{T}} \in \mathbb{C}^M$, where $M = NL$ corresponds to the total number of antennas within the coverage area. For each coherence block, an independent realization of correlated Rayleigh fading is generated as $\mathbf{h}_{kl} \sim \mathcal{N}_{\mathbb{C}}\left(\mathbf{0}, \mathbf{R}_{kl}\right)$, where $\mathbf{R}_{kl} \in \mathbb{C}^{N\times N}$ is the spatial correlation matrix. The Gaussian distribution models the small-scale fading, while the positive semi-definite correlation matrix $\mathbf{R}_{kl}$ captures the large-scale fading effects, including geometric path loss, shadowing, antenna gains, and spatial channel correlation. Assuming that channel vectors from different APs are independently distributed, we have $\mathbb{E}\left\{\mathbf{h}_{kn}\left(\mathbf{h}_{kl}\right)^{\mathrm{H}}\right\} = 0$ for $l \neq n$. This assumption is reasonable due to the spatial distribution of APs within the network. The collective channel follows the distribution:

$$\mathbf{h}_k \sim \mathcal{N}_{\mathbb{C}}\left(\mathbf{0}, \mathbf{R}_k\right), \tag{3.1}$$

where $\mathbf{R}_k = \mathrm{diag}\left(\mathbf{R}_{k1}, \ldots, \mathbf{R}_{kL}\right) \in \mathbb{C}^{M\times M}$ is the block diagonal spatial correlation matrix. The channel vectors for different UEs are independently distributed. We assume that there are τ_p mutually orthogonal pilot sequences of length τ_p, with τ_p being a constant independent of K^2. Pilots are assigned to UEs upon their entry into the network. Let $\mathcal{S}_t \subset \{1, \ldots, K\}$ represent the subset of UEs assigned to pilot t. When these UEs transmit their pilot sequence, the received signal at AP l after despreading, denoted as $\mathbf{y}_{tl}^{\mathrm{pilot}} \in \mathbb{C}^N$, is given by [6]:

$$\mathbf{y}_{tl}^{\mathrm{pilot}} = \sum_{i\in\mathcal{S}_t} \sqrt{\tau_p p_i}\mathbf{h}_{il} + \mathbf{n}_{tl}, \tag{3.2}$$

where p_i is the transmit power of the UE i, τ_p is the processing gain, and $\mathbf{n}_{tl} \sim \mathcal{N}_{\mathbb{C}}\left(\mathbf{0}, \sigma^2\mathbf{I}_N\right)$ represents the thermal noise. The minimum mean-squared-error (MMSE) estimate of $\mathbf{h}_{kl}$ for $k \in \mathcal{S}_t$ is:

$$\widehat{\mathbf{h}}_{kl} = \sqrt{p_k\tau_p}\mathbf{R}_{kl}\mathbf{\Psi}_{tl}^{-1}\mathbf{y}_{tl}^{\mathrm{pilot}}, \tag{3.3}$$

where

$$\boldsymbol{\Psi}_{tl} = \mathbb{E}\left\{\mathbf{y}_{tl}^{\text{pilot}}\left(\mathbf{y}_{tl}^{\text{pilot}}\right)^{\mathrm{H}}\right\} = \sum_{i\in\mathcal{S}_t}\tau_p p_i \mathbf{R}_{il} + \sigma^2\mathbf{I}_N \tag{3.4}$$

is the correlation matrix. The mutual interference caused by UEs sharing the same pilot in $\mathcal{S}_t$ results in pilot contamination, which degrades system performance similarly to traditional Massive MIMO systems. Pilot contamination has two primary effects: it reduces the quality of channel estimation, making coherent transmission less effective, and it causes the estimates $\widehat{\mathbf{h}}_{kl}$ for $k \in \mathcal{S}_t$ to become correlated, leading to additional interference. While both effects impact UEs performance, only the latter contributes to what is known as coherent interference.

It is crucial to emphasize that our channel model is fundamentally based on the distance between the APs and UEs. In this model, the strength of the channel gain is inversely related to the distance between an AP and a UE. Specifically, the UE that is geographically closest to a particular AP experiences the highest channel gain from that AP. This proximity-based characteristic ensures that the signal quality and reliability are maximized for UEs near the AP, while those farther away experience progressively weaker channel gains. Consequently, this model effectively captures the spatial variations in signal strength that occur in real-world wireless networks, where path loss and attenuation increase with distance.

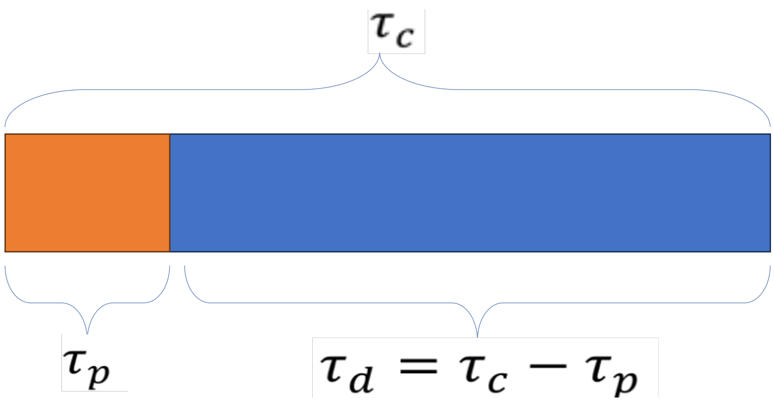


FIGURE 3.3: TDD Communication Block Model: τ_p is the pilot transmission phase and τ_d is the data transmission phase.

3.3.2 *Uplink Channel Model*

Here, we describe the uplink channel model, which is a critical component in the analysis and design of distributed Massive MIMO systems. The uplink channel refers to the communication link from the UE to the APs. During UL data transmission, the received signal $\mathbf{y}_l^{\text{ul}} \in \mathbb{C}^N$ at APl is

$$\mathbf{y}_l^{\text{ul}} = \sum_{i=1}^{K}\mathbf{h}_{il}s_i + \mathbf{n}_l \tag{3.5}$$

where $s_i \in \mathbb{C}$ is the signal transmitted from UE i with power p_i and $\mathbf{n}_l \sim \mathcal{CN}\left(\mathbf{0}, \sigma^2 \mathbf{I}_N\right)$ [6].

3.3.3 Downlink Channel Model

The downlink channel model describes the communication link from the APs to the UEs, which is equally vital in the context of distributed Massive MIMO systems. Let $\mathbf{w}_{il} \in \mathbb{C}^N$ represent the pre-coding vector assigned by AP l to UE i. During downlink (DL) transmission, the signal received at UE k is expressed as:

$$y_k^{\mathrm{dl}} = \sum_{l=1}^{L} \mathbf{h}_{kl}^{\mathrm{H}} \sum_{i=1}^{K} \mathbf{w}_{il} \varsigma_i + n_k = \mathbf{h}_k^{\mathrm{H}} \sum_{i=1}^{K} \mathbf{w}_i \varsigma_i + n_k, \tag{3.6}$$

where $\varsigma_i \in \mathbb{C}$ denotes the independent unit-power data signal intended for UE i (i.e., $\mathbb{E}\left\{\|\varsigma_i\|^2\right\} = 1$), $\mathbf{w}_i = \left[\mathbf{w}_{i1}^{\mathrm{T}} \ldots \mathbf{w}_{iL}^{\mathrm{T}}\right]^{\mathrm{T}} \in \mathbb{C}^M$ is the overall pre-coding vector, and $n_k \sim \mathcal{N}_{\mathbb{C}}\left(0, \sigma^2\right)$ is the receiver noise. Given the distribution of $\mathbf{h}_k$, the system model is mathematically equivalent to a DL single-cell Massive MIMO system with correlated fading. Consequently, the achievable downlink SE in a distributed Massive MIMO setup can be derived from existing results on Massive MIMO with correlated fading. Similar to the uplink, the key distinction between distributed and cellular networks lies in the design of the pre-coding vectors, which must rely solely on local CSI and adhere to per-AP power constraints. The most common approach is Maximum Ratio (MR) pre-coding, defined as:

$$\mathbf{w}_{il} = \sqrt{\rho_i} \frac{\widehat{\mathbf{h}}_{il}}{\sqrt{\mathbb{E}\left\{\left\|\widehat{\mathbf{h}}_{il}\right\|^2\right\}}}, \tag{3.7}$$

where $\rho_i \geq 0$ represents the transmit power allocated to UE i [6].

3.3.4 Assumptions and Constraints

The performance and scalability of distributed Massive MIMO networks are influenced by several critical constraints that challenge network performance. One of the primary constraints is pilot contamination, a phenomenon that arises in TDD systems where the reuse of pilot sequences across different UEs leads to inter-UE interference. This interference degrades the accuracy of channel estimation, which is particularly problematic in dense network environments where numerous UEs are served simultaneously. As the network's UE density increases, the likelihood of pilot contamination grows, significantly impacting the overall system performance. To mitigate the pilot contamination problem, we assume that each AP is limited to serving a maximum of τ_p UEs, where τ_p represents the length of the pilot sequence. This restriction helps reduce the likelihood of interference but also limits the number of UEs that can be effectively served by each AP.

Another key constraint is the limited availability of AP resources. In distributed Massive MIMO networks, the finite number of APs must be smartly allocated to serve a potentially large number of UEs. Unlike traditional cellular networks where APs are fixed to specific cells, the distributed nature of this system requires careful management of AP-UE allocation to maximize spectral efficiency and minimize interference. The limitation on AP resources becomes more significant as UE density increases, further complicating network management. Each UE seeks to be served by an optimal set of APs, but when the UE density is high, each AP is required to serve more UEs, leading to two critical challenges. First, the limited number of available pilots increases the risk of pilot contamination, where UEs sharing the same pilots cause inter-UE interference, degrading overall network performance. Second, the increased signaling and data processing required as each AP serves more UEs results in higher computational costs, straining the network's efficiency. These constraints make smart AP selection essential, particularly in high-density scenarios, to balance performance with resource allocation and computational costs. This need for intelligent AP selection strategies is the central focus of our work, as we aim to address the challenges that arise when the number of UEs far exceeds the available APs, ensuring that Distributed Massive MIMO systems remain viable and efficient under these demanding conditions.

3.4 EVALUATION METRICS

To comprehensively assess the performance of scalable distributed massive MIMO networks, it is crucial to evaluate various metrics that reflect both the system's efficiency and its practical feasibility. This section outlines the key metrics used to quantify the effectiveness of such systems, focusing on their spectral efficiency. Spectral efficiency measures the data throughput capabilities of the system. By analyzing spectral efficiency, we can tell how well the system performs under different scenarios and identify areas for improvement.

3.4.1 Spectral Efficiency

Spectral efficiency is a fundamental performance metric in wireless communication systems, quantifying the amount of data transmitted per unit of bandwidth. In the context of scalable distributed massive MIMO, it is essential to understand how efficiently the system utilizes the available spectrum to deliver high-quality service. This subsection is divided into three parts, each addressing a different aspect of spectral efficiency. As for the mathematical models of the SE in terms of Signal-to-Interference-plus-Noise Ratio (SINR) on the uplink and the downlink, we use the models from [6]:

- On the Uplink: When the MMSE channel estimates are known, an achievable SE of UE k is

$$\mathrm{SE}_k^{(\mathrm{ul},1)} = \frac{1}{\tau_c}\mathbb{E}\left\{\log_2\left(1+\mathrm{SINR}_k^{(\mathrm{ul},1)}\right)\right\} \tag{3.8}$$

where the instantaneous effective signal-to-interference-and noise ratio (SINR) is given by

$$\mathrm{SINR}_k^{(\mathrm{ul},1)} = \frac{p_k \left| \mathbf{v}_k^{\mathrm{H}} \mathbf{D}_k \widehat{\mathbf{h}}_k \right|^2}{\sum_{i=1, i\neq k}^{K} p_i \left| \mathbf{v}_k^{\mathrm{H}} \mathbf{D}_k \widehat{\mathbf{h}}_i \right|^2 + \mathbf{v}_k^{\mathrm{H}} \mathbf{Z}_k \mathbf{v}_k} \tag{3.9}$$

$$\text{with } \mathbf{Z}_k = \mathbf{D}_k \left(\sum_{i=1}^{K} p_i \mathbf{C}_i + \sigma_{\mathrm{ul}}^2 \mathbf{I}_{LN} \right) \mathbf{D}_k \tag{3.10}$$

where $\mathbf{D}_k = \mathrm{diag}\left(\mathbf{D}_{k1}, \ldots, \mathbf{D}_{kL}\right) \in \mathbb{C}^{M\times M}$ is a block-diagonal matrix. $\mathbf{v}_k = \left[\begin{array}{ccc} \mathbf{v}_{k1}^{\mathrm{T}} & \ldots & \mathbf{v}_{kL}^{\mathrm{T}} \end{array} \right]^{\mathrm{T}} \in \mathbb{C}^M$ denotes the collective combining vector. p_i is the transmit power of UE i.

- On the Downlink: An achievable DL SE for UE k is given by

$$\mathrm{SE}_k^{(\mathrm{dl})} = \frac{1}{\tau_c} \log_2 \left(1 + \mathrm{SINR}_k^{(\mathrm{dl})} \right) \tag{3.11}$$

where

$$\mathrm{SINR}_k^{(\mathrm{dl})} = \frac{\rho_k \left| \mathbb{E}\left\{ \mathbf{h}_k^{\mathrm{H}} \mathbf{D}_k \overline{\mathbf{w}}_k \right\} \right|^2}{\sum_{i=1}^{K} \rho_i \mathbb{E}\left\{ \left| \mathbf{h}_k^{\mathrm{H}} \mathbf{D}_i \overline{\mathbf{w}}_i \right|^2 \right\} - \rho_k \left| \mathbb{E}\left\{ \mathbf{h}_k^{\mathrm{H}} \mathbf{D}_k \overline{\mathbf{w}}_k \right\} \right|^2 + \sigma_{\mathrm{dl}}^2} \tag{3.12}$$

and the expectations are with respect to the channel realizations. $\mathbf{D}_k = \mathrm{diag}\left(\mathbf{D}_{k1}, \ldots, \mathbf{D}_{kL}\right) \in \mathbb{C}^{M\times M}$ is a block-diagonal matrix. $\rho_i \geq 0$ represents the transmit power allocated to UE i.

3.4.1.1 *Spectral Efficiency per User*

Spectral Efficiency per user, or SE per UE, is a critical metric in evaluating the performance of wireless communication systems. It quantifies how efficiently the available spectrum is utilized by each individual user in the network. In our analysis, SE per UE is calculated as the average achievable spectral efficiency across multiple time stamps, offering a comprehensive view of the network's ability to support high data rates for each user over time. The SE per UE is derived by taking into account the instantaneous data rate achieved by a specific UE at each time stamp, relative to the bandwidth utilized. By averaging the SE over time, we obtain a stable and meaningful measure that reflects the overall performance experienced by the user, rather than momentary peaks or troughs that might occur due to transient conditions. This metric is particularly valuable in assessing how well the network can maintain consistent performance for each UE, regardless of its position or the specific APs it connects to. It also helps in identifying any disparities in service quality among users, which might arise due to uneven resource distribution, interference, or varying channel conditions. By analyzing SE per UE, network designers can make informed decisions on optimizing the deployment of APs, the allocation of resources, and the configuration of transmission schemes to ensure fair and efficient use of the spectrum across all users.

3.4.1.2 *Sum Spectral Efficiency*

Sum Spectral Efficiency (Sum SE) is a fundamental metric used to evaluate the overall performance of a wireless communication network. It provides a holistic measure of how efficiently the network utilizes its available spectrum to serve all connected users simultaneously. Specifically, Sum SE is calculated as the averaged summation of the SEs of all UEs at a given time stamp. This calculation is repeated over multiple time stamps to account for temporal variations in the network, resulting in an average Sum SE that reflects the network's overall capacity. The Sum SE metric is particularly valuable in scenarios where the collective performance of the network is of interest, such as in dense environments or industrial settings with high UE densities. By summing the SEs of all UEs, this metric captures the total capacity of the network. This is crucial for understanding the network's ability to meet the demands of high-traffic scenarios and to identify potential bottlenecks in resource allocation. Moreover, Sum SE is often used as a benchmark to compare different AP selection methods or network configurations. By analyzing the Sum SE, network designers can assess the trade-offs between individual user performance and overall network efficiency, guiding decisions on how to optimize network design for maximum capacity.

3.4.1.3 *95% Likely Spectral Efficiency*

The 95% Likely Spectral Efficiency (95% Likely SE) is a key performance metric used to assess the reliability and consistency of spectral efficiency across a network. This metric specifically focuses on the lower tail of the SE distribution, representing the SE value that 95% of the UEs are likely to achieve or exceed, making it an essential metric for evaluating the robustness of a network. The 95% Likely SE is particularly important in scenarios where user experience must be consistently high, even under challenging conditions such as high user densities. By focusing on the SE that the majority of users can expect to achieve, this metric helps ensure that the network design not only maximizes overall capacity but also delivers acceptable performance levels to nearly all users. To calculate the 95% Likely SE, the SEs of all UEs are first computed and then sorted in ascending order. The SE value at the 5th percentile of this sorted list is identified, which represents the 95% Likely SE. This process is typically repeated across multiple time stamps to account for temporal fluctuations in the network, resulting in an averaged 95% Likely SE that reflects the network's performance under typical operating conditions. In distributed massive MIMO systems, where the network consists of APs serving a large number of UEs, the 95% Likely SE is a critical measure of how well the network handles varying user demands and environmental conditions. A higher 95% Likely SE suggests that the network is effectively managing its resources and minimizing the impact of adverse conditions on user performance, thereby ensuring that most users receive a satisfactory level of service. This metric is also valuable for comparing different AP selection strategies or network configurations. By analyzing the 95% Likely SE, network designers can identify approaches that not only maximize overall spectral efficiency but also ensure that the network provides reliable and consistent performance to nearly all users, regardless of their location or channel quality.

4

AP Selection Methods

In this chapter, we explore the various methods of AP selection in our network. Firstly, Section 4.1 explains the new Fair AP Request method, which we developed in this work and which aims to ensure a balanced load distribution among APs while achieving higher performance levels for all UEs. In Section 4.2, we present the baseline and reference AP selection methods used for the comparative analysis. This section sets the stage for the comparative performance analysis in the results chapter, allowing us to understand the relative merits of different AP selection methods. Lastly, in Section 4.3 we provide an overview of the computational complexities of the algorithms behind the AP selection methods.

4.1 Fair AP Request

In this section, we design the Fair AP Request method, an AP selection strategy developed during this thesis, to address some of the key challenges in Distributed Massive MIMO networks. The Fair AP Request aims to balance the network load more effectively by ensuring a fair distribution of UEs across available APs, thereby optimizing both spectral efficiency and system performance. It also aims to better utilize and exploit the available networks resources in order to achieve the best possible performance, especially for weaker UEs.

It's worth highlighting that our definition of "Fairness" diverges from the traditional interpretation found in the literature. In our work, "Fairness" signifies that the majority of UEs enjoy a consistent level of performance, irrespective of their location or the conditions they face.

The Fair AP Request method functions by dynamically assigning UEs to APs based on the quality of the channel conditions, while also considering the number of UEs each AP is already serving. This approach mitigates the issue of overloading certain APs, which is a common drawback in other AP selection methods, and ensures that the network resources are utilized more equitably. By integrating fairness into the AP selection process, this method can achieve significant performance gains, particularly in scenarios with high user densities or variable network conditions.

The core idea of Fair AP Request is to allow UEs to request service from APs that not only provide strong signal quality but are also underutilized in terms of the number of UEs they are serving. This dual consideration helps in preventing scenarios where certain APs become bottlenecks due to excessive demand, while others remain underutilized. As a result, this method can provide better load balancing, which is crucial for maintaining high network performance, especially in dense environments.

Fair AP Request has proven to be advantageous over other AP selection methods in various scenarios, as will be demonstrated in Chapter 5. Its ability to adapt to changing network conditions while maintaining fairness among APs makes it a robust and scalable solution for Distributed Massive MIMO.

Here is the pseudocode for the Fair AP Request method:

Algorithm 1 Fair AP Request

Inputs: Number of UEs K, Initial number of AP requests G, Maximum number of UEs each AP can serve X, Number of APs L

for each UE $k = 1$ to K **do**
    Initialize $ServingAPs \leftarrow 0$
    for each AP request $g = 1$ to initial G **do**
        $candiAP \leftarrow$ AP corresponding to the g-th closest distance
        if AP $candiAP$ is serving fewer than X UEs **then**
            Assign AP $candiAP$ to serve UE k
            $D[k, candiAP] \leftarrow 1$
        else
            $WorstUE \leftarrow$ Find the UE with the worst channel gain at $candiAP$
            if Channel gain of UE_k is better than $WorstUE$ **then**
                Disconnect $WorstUE$
                $D[WorstUE, candiAP] \leftarrow 0$
                Assign AP $candiAP$ to serve UE_k
                $D[k, candiAP] \leftarrow 1$
            end if
        end if
        $ServingAPs \leftarrow ServingAPs + 1$
    end for
end for
Fairness Step: Sort UEs from weakest to strongest by channel gain and distance to APs with available capacity
for each AP a with available capacity **do**
    while sum$(D[:, a]) < X$ **do**
        Connect the weakest nearest UE to a until the limit X is reached,
        Update D accordingly
    end while
end for

Output: AP-UE allocation matrix D

The following detailed description provides a detailed logical flow of the Fair AP Request algorithm:

- **Initialization (Input Parameters):**
  - The algorithm begins by taking the following input parameters:

    * K: The total number of UEs that need to be served.
    * G: The initial number of AP requests that each UE will make.
    * X: The maximum number of UEs that any single AP can serve.
    * L: The total number of APs in the network.
  - These inputs define the constraints within which the algorithm operates, including the limits on AP capacity and the number of initial requests each UE can make.

- **Step 1: Iterating Over Each UE**
  - The first `for` loop iterates over each UE from 1 to K. This loop ensures that the AP selection process is applied to every UE in the network individually.
- **Step 2: Initialize the ServingAPs Counter**
  - For each UE, the `ServingAPs` counter is initialized to zero. This counter tracks how many APs have been assigned to serve the current UE so far.
- **Step 3: Iterating Over Initial AP Requests**
  - The second `for` loop iterates over each of the initial G AP requests for the current UE. This loop is responsible for evaluating potential APs based on their proximity to the UE.
- **Step 4: Identifying the Candidate AP**
  - For each request, the algorithm identifies the candidate AP (`candiAP`) corresponding to the g-th closest AP to the UE k.
- **Step 5: Checking AP Capacity**
  - The algorithm checks if the candidate AP is currently serving fewer than X UEs. If the AP has available capacity, it can be assigned to the current UE.
- **Step 6 - 8: Assigning the AP to Serve the UE**
  - If the candidate AP has available capacity, it is assigned to serve the current UE. The algorithm updates the AP-UE allocation matrix $D(k, \texttt{candiAP})$ by setting the corresponding entry to 1, indicating that this AP is now serving this UE.
- **Step 9 - 16: Handling AP Overload**
  - If the candidate AP has already reached its capacity, the algorithm identifies the UE with the worst channel gain currently served by this AP (`WorstUE`).
  - If the current UE k has a better channel gain than `WorstUE`, the AP disconnects `WorstUE` and instead serves UE k. The allocation matrix D is updated accordingly.
- **Step 17 - 19: Incrementing the ServingAPs Counter**

- After an AP has been assigned to the current UE, the `ServingAPs` counter is incremented.

- **Step 20 (Fairness Step): Sorting and Reallocating Resources**
  - Once the initial assignment is complete for all UEs, the algorithm performs a fairness step. It sorts UEs from weakest to strongest based on their channel gain and distance to APs with available capacity. This step ensures that weaker UEs, which may have been disadvantaged during the initial assignment, receive additional resources.

- **Step 21 - 26: Allocating Remaining Capacity to the Weakest UEs**
  - The algorithm iterates over each AP that still has available capacity. It connects the weakest nearest UEs to these APs until the APs reach their maximum serving limit X. The allocation matrix D is updated to reflect these connections.

- **Final Output: AP-UE Allocation Matrix** $D(K, L)$
  - After all steps, including the fairness adjustment, have been completed, the algorithm outputs the AP-UE allocation matrix $D(K, L)$. This matrix indicates which APs are assigned to which UEs.

In summary, the Fair AP Request method is a significant advancement in AP selection strategies, offering a balanced approach to handling the complexities of Distributed Massive MIMO networks. As Chapter 5 will show, this method consistently outperforms other AP selection methods in many scenarios, particularly in terms of fairness, load balancing, and overall network performance.

4.2 BASELINE AND REFERENCE AP SELECTION METHODS

In this section, we present and explain the baseline and reference AP selection methods against which the proposed Fair AP Request method will be evaluated. These methods serve as critical benchmarks for understanding the performance and efficiency of AP selection strategies within Distributed Massive MIMO networks. By comparing our approach to these established methods, we can better highlight the improvements and advantages offered by the Fair AP Request method.

The baseline and reference AP selection methods typically include approaches that are either widely used in current network architectures or represent theoretical ideals. These methods provide a spectrum of AP selection strategies, from simple and static models to more dynamic and complex approaches. Understanding how these methods function, their advantages, and their limitations is crucial for contextualizing the performance of any new AP selection strategy.

By examining the performance of the Fair AP Request method against these baseline and reference methods as we will see in Chapter 5, we aim to demonstrate the specific advantages of our approach, particularly in terms of load balancing, fairness, and overall network efficiency. The results from these comparisons will be crucial in validating the effectiveness of the Fair AP Request method under various network conditions and constraints.

4.2.1 G APs

In this subsection, we look into the "G APs" method, which is the most basic AP selection method examined in this thesis [6]. The "G APs" method is designed to assign each UE to a fixed number of APs, specifically the nearest G APs in terms of geographical distance or channel quality. This method is a useful benchmark for evaluating more advanced AP selection strategies.

The "G APs" method operates on the principle of proximity. For each UE in the network, the algorithm identifies the G closest APs based on distance or channel quality metrics. These G APs are then assigned to serve the UE, ensuring that every UE has a fixed number of APs providing service. This method does not consider factors such as the load on individual APs or the overall distribution of UEs across the network, which can lead to inefficiencies in networks with uneven UE distributions.

The following pseudocode outlines the steps involved in the "G APs" method:

Algorithm 2 G APs [6]

Inputs: Number of APs L, Number of UEs K, Number of nearest APs to select G, Maximum number of UEs an AP can serve X

```
for each UE k = 1 to K do
    Identify the set t_n of the G nearest APs to UE k
    for each AP m in t_n do
        if AP m is serving fewer than X UEs then
            Assign AP m to serve UE k by setting D(k, m) ← 1
        end if
    end for
end for
```

Output: AP-UE allocation matrix $D(K, L)$

The following detailed description provides a detailed logical flow of the G APs algorithm:

- **Initialization (Input Parameters):**
  - The algorithm begins with several input parameters:
    - L: The total number of APs in the network.
    - K: The total number of UEs that need to be served.
    - G: The number of nearest APs to select for each UE.
    - X: The maximum number of UEs that any single AP can serve.
  - These inputs define the network's structure and the constraints that the algorithm must respect during the AP selection process.

- **Step 1: Iterating Over Each UE**
  - The first `for` loop iterates over each UE from 1 to K. This loop ensures that the algorithm individually processes each UE in the network. The goal in each iteration is to identify the G nearest APs to the current UE and assign them to serve the UE, if possible.
- **Step 2: Identifying the Set t_n of Nearest APs**
  - For each UE k, the algorithm identifies the set t_n of the G nearest APs based on proximity (e.g., distance or signal strength). This step involves computing the distances from the UE to all APs and selecting the closest G APs. The set t_n contains the indices of these G APs.
- **Step 3: Iterating Over Each AP in t_n**
  - The second `for` loop iterates over each AP m in the set t_n of nearest APs. The purpose of this loop is to evaluate whether each selected AP m has the capacity to serve the current UE k.
- **Step 4: Checking AP Capacity**
  - The algorithm checks if AP m is currently serving fewer than X UEs. This is a crucial constraint, as no AP can serve more than X UEs. If AP m has available capacity (i.e., is serving fewer than X UEs), the algorithm proceeds to the next step.
- **Step 5 - 8: Assigning the AP to Serve the UE**
  - If the capacity check is satisfied, AP m is assigned to serve UE k. This assignment is recorded by setting the corresponding element in the AP-UE allocation matrix $D(k, m)$ to 1, indicating that AP m is now serving UE k.
- **Final Output: AP-UE Allocation Matrix $D(K, L)$**
  - After processing all UEs and their nearest APs, the algorithm outputs the AP-UE allocation matrix $D(K, L)$. This matrix has dimensions $K \times L$, where each entry $D(k, m) = 1$ indicates that AP m is assigned to serve UE k. Entries with $D(k, m) = 0$ indicate that AP m is not serving UE k.

By comparing more advanced methods against this straightforward approach, we can better understand the benefits of incorporating additional factors such as load balancing, fairness, and dynamic AP selection into the network design.

The "G APs" method serves as a foundational AP selection strategy within the context of Distributed Massive MIMO networks. However, its performance is limited by its lack of consideration for AP load balancing and other dynamic factors. As we explore more advanced AP selection methods in subsequent sections, the "G APs" method provides a critical reference point, highlighting the potential gains achieved by incorporating more critical selection criteria.

4.2.2 *Dynamic AP Request*

The Dynamic AP Request method is designed to provide a more flexible and responsive approach to AP selection compared to simpler methods like "G APs" [15]. In this method, each UE dynamically requests service from a G number of APs that offer the best channel conditions. This method begins by each UE sending out requests to the G APs that are expected to offer the most favorable channel conditions. Upon receiving these requests, the APs evaluate the current load, their remaining capacity, and the channel gain associated with each UE. If the APs have available capacity, they accept the UE's request and establish a connection. If not, the UE continues to request service from other APs within its range until it finds an available one or exhausts its options.

The following pseudocode illustrates the steps involved in the Dynamic AP Request method:

Algorithm 3 Dynamic AP Request [15]

Inputs: Number of APs L, Number of UEs K, Target number of APs to serve each UE G, Maximum number of UEs an AP can serve X

for each UE $k = 1$ to K **do**
    Initialize $ServingAPs = 0$
    for each AP $m = 1$ to L (sorted by distance) **do**
        $candiAP \leftarrow$ AP corresponding to the m-th closest distance to UE k
        if AP $candiAP$ is serving fewer than X UEs **then**
            Assign AP $candiAP$ to serve UE k by setting $D(k, candiAP) \leftarrow 1$
            $ServingAPs \leftarrow ServingAPs + 1$
        end if
        if $ServingAPs = G$ **then**
            break
        end if
    end for
end for

Output: AP-UE allocation matrix $D(K, L)$

- **Initialization (Input Parameters):**
  - The algorithm begins with several input parameters:
    - L: The total number of APs in the network.
    - K: The total number of UEs that need to be served.
    - G: The target number of APs that should serve each UE.
    - X: The maximum number of UEs that any single AP can serve.
  - These inputs establish the framework within which the algorithm operates, defining the network's structure and the constraints for AP selection.
- **Step 1: Iterating Over Each UE**
  - The first `for` loop iterates over each UE from 1 to K. This loop ensures that the algorithm processes each UE individually, assigning the appropriate number of APs to each one.

- **Step 2: Initialize the ServingAPs Counter**
  - For each UE, the `ServingAPs` counter is initialized to zero. This counter keeps track of how many APs have been successfully assigned to serve the current UE.
- **Step 3: Iterating Over Each AP (Sorted by Distance)**
  - The second `for` loop iterates over each AP m from 1 to L. The APs are considered in the order of their proximity to the current UE, with $m = 1$ representing the closest AP and $m = L$ representing the furthest. The purpose of this loop is to evaluate whether each AP can serve the UE, with the aim of selecting the closest APs until the target number G is reached.
- **Step 4: Identifying the Candidate AP**
  - The algorithm identifies the candidate AP (`candiAP`) corresponding to the m-th closest distance to the UE k. This AP is considered for assignment to the current UE.
- **Step 5: Checking AP Capacity**
  - The algorithm checks if the candidate AP is currently serving fewer than X UEs. This check ensures that the AP has the capacity to serve another UE without exceeding its limit. If the AP has available capacity, the algorithm proceeds to the next step.
- **Step 6: Assigning the AP to Serve the UE**
  - If the candidate AP has capacity, it is assigned to serve the current UE. This assignment is recorded by setting the corresponding element in the AP-UE allocation matrix $D(k, \texttt{candiAP})$ to 1, indicating that AP `candiAP` is now serving UE k.
- **Step 7: Incrementing the ServingAPs Counter**
  - After successfully assigning an AP to the current UE, the `ServingAPs` counter is incremented by one. This step tracks how many APs have been assigned to the UE so far.
- **Step 8 - 13: Checking if the Target Number of APs has been Reached**
  - The algorithm checks if the `ServingAPs` counter has reached the target number G. If the UE has been successfully assigned to G APs, the algorithm breaks out of the loop, stopping further consideration of additional APs. This ensures that the UE is served by exactly G APs, if possible.
- **Final Output: AP-UE Allocation Matrix $D(K, L)$**

- After processing all UEs and their nearest APs, the algorithm outputs the AP-UE allocation matrix $D(K, L)$. This matrix has dimensions $K \times L$, where each entry $D(k, \texttt{candiAP}) = 1$ indicates that AP `candiAP` is assigned to serve UE k. Entries with $D(k, \texttt{candiAP}) = 0$ indicate that AP `candiAP` is not serving UE k.

While the Dynamic AP Request method represents a significant improvement over static approaches, it has notable shortcomings, particularly when compared to "Fair AP Request".

- **In Step 3 of Dynamic AP Request:** The algorithm iterates over APs in the order of their proximity to the UE, assigning APs until the target number G is reached. However, this method does not account for the overall network performance, it simply allocates APs based on proximity without considering the load distribution or channel quality beyond the initial assignment.
- **In contrast, in Step 9 of Fair AP Request:** After selecting the initial G APs based on proximity, the method evaluates whether the selected AP is already serving the maximum number of UEs. If the AP is overloaded, the algorithm compares the current UE's channel gain with the UE that has the worst channel gain at that AP (Step 10). This ensures that the AP serves the UE with the better channel gain, optimizing the network's performance by reassigning resources to those who can benefit the most.
- **Dynamic AP Request in Step 6:** The method does not provide any mechanism to reconsider the AP allocation if a UE ends up with less favorable conditions after the initial allocation. Fair AP Request, on the other hand, introduces a fairness adjustment step (Step 20), where UEs are sorted from weakest to strongest based on channel conditions, and remaining resources are reallocated to the weakest UEs. This step ensures that even UEs with initially poor conditions receive additional resources, balancing the load more effectively and improving overall network performance.
- **In Step 13 of Dynamic AP Request:** The algorithm stops assigning APs once the target G APs have been allocated, without considering if other UEs may have been assigned to those APs with better channel conditions. Fair AP Request, in contrast, revisits the AP assignments during its fairness step (Steps 20-26), actively reallocating available AP resources to UEs with weaker channel gains, thus ensuring a more equitable distribution of network resources.

Overall, the Fair AP Request method addresses the shortcomings of the Dynamic AP Request by not only considering immediate channel conditions but also by implementing mechanisms to balance the network load, reallocate underutilized APs, and improve fairness across all UEs. This approach results in better overall network performance, especially in high-density scenarios, where effective resource management is crucial.

4.2.3 *Adaptive AP Request*

The Adaptive AP Request method introduces a more refined approach to AP selection by considering not only the current channel conditions but also the capacity constraints of the APs [15]. In this method, each UE initiates a connection request to a G number of APs based on the best channel conditions available. However, unlike the Dynamic AP Request method, the Adaptive AP Request adds another layer of decision-making.

When an AP receives a connection request, it evaluates its current load and determines whether it can accommodate the new UE. If the AP has reached its capacity limit, it doesn't automatically reject the request. Instead, the AP compares the channel conditions of the incoming UE with those of the UEs it is already serving. If the new UE has better channel conditions than one of the currently served UEs, the AP may disconnect the UE with the worst channel conditions and replace it with the new UE. This adaptive mechanism allows the network to optimize the allocation of resources dynamically, ensuring that the UEs with the best possible conditions are served.

The following pseudocode outlines the steps involved in the "Adaptive AP Request" method:

Algorithm 4 Adaptive AP Request [15]

Inputs: Number of UEs K, Initial number of AP requests G, Maximum number of UEs each AP can serve X, Number of APs L

for each UE $k = 1$ to K **do**
    Initialize $ServingAPs \leftarrow 0$
    for each AP request $g = 1$ to G **do**
        $candiAP \leftarrow$ AP corresponding to the g-th closest distance
        if AP $candiAP$ is serving fewer than X UEs **then**
            Assign AP $candiAP$ to serve UE k
            $D[k, candiAP] \leftarrow 1$
        else
            $WorstUE \leftarrow$ Find the UE with the worst channel gain at $candiAP$
            if Channel gain of UE_k is better than $WorstUE$ **then**
                Disconnect $WorstUE$
                $D[WorstUE, candiAP] \leftarrow 0$
                Assign AP $candiAP$ to serve UE_k
                $D[k, candiAP] \leftarrow 1$
            end if
        end if
        $ServingAPs \leftarrow ServingAPs + 1$
    end for
end for

Output: AP-UE allocation matrix D

---

1. **Initialization (Input Parameters):**

- The algorithm begins by accepting the following input parameters:
  - K: The total number of UEs that need to be served.
  - G: The initial number of AP requests that each UE will make.
  - X: The maximum number of UEs that any single AP can serve.
  - L: The total number of APs in the network.
- These inputs define the framework within which the algorithm operates, including the limits on AP capacity and the number of initial requests each UE can make.

2. **Step 1: Iterating Over Each UE**
   - The first `for` loop iterates over each UE from 1 to K. This loop ensures that the AP selection process is applied individually to every UE in the network.

3. **Step 2: Initialize the ServingAPs Counter**
   - For each UE, the `ServingAPs` counter is initialized to zero. This counter tracks how many APs have been successfully assigned to serve the current UE.

4. **Step 3: Iterating Over Initial AP Requests**
   - The second `for` loop iterates over the initial G AP requests for the current UE. This loop is responsible for evaluating potential APs based on their proximity to the UE.

5. **Step 4: Identifying the Candidate AP**
   - For each request, the algorithm identifies the candidate AP (`candiAP`) corresponding to the g-th closest AP to the UE k.

6. **Step 5: Checking AP Capacity**
   - The algorithm checks if the candidate AP is currently serving fewer than X UEs. If the AP has available capacity, it can be assigned to the current UE.

7. **Step 6 - 8: Assigning the AP to Serve the UE**
   - If the candidate AP has available capacity, it is assigned to serve the current UE. The algorithm updates the AP-UE allocation matrix $D(k, \texttt{candiAP})$ by setting the corresponding entry to 1, indicating that this AP is now serving this UE.

8. **Step 9 - 16: Handling AP Overload**
   - If the candidate AP has already reached its capacity, the algorithm identifies the UE with the worst channel gain currently served by this AP (`WorstUE`).
   - If the current UE k has a better channel gain than `WorstUE`, the AP disconnects `WorstUE` and instead serves UE k. The allocation matrix D is updated accordingly to reflect these changes.

9. **Step 17 - 19: Incrementing the ServingAPs Counter**
   - After an AP has been assigned to the current UE, the `ServingAPs` counter is incremented. This step ensures that the UE continues to request additional APs until the desired number G is reached or no more suitable APs are available.
10. **Final Output: AP-UE Allocation Matrix $D(K, L)$**
    - After processing all UEs and their nearest APs, the algorithm outputs the AP-UE allocation matrix $D(K, L)$. This matrix indicates which APs are assigned to which UEs, taking into account both proximity and channel conditions to optimize overall network performance.

While the Adaptive AP Request method offers a more advanced approach than the Dynamic AP Request by actively managing AP resources and attempting to optimize service quality, it still falls short of the optimal balance provided by the "Fair AP Request" method.

- **In Step 9 of Adaptive AP Request:** The algorithm reallocates resources by disconnecting the UE with the worst channel gain if a new UE has a better channel gain. However, this approach primarily focuses on optimizing service quality for individual UEs based on immediate channel conditions, potentially leading to an uneven distribution of network resources.
- **In contrast, in Step 20 of Fair AP Request:** The method introduces a fairness adjustment where UEs are sorted based on their channel gain and distance to available APs. This step ensures that weaker UEs, which may have been disadvantaged in the initial allocation, receive additional resources, thereby improving overall network performance.
- **Adaptive AP Request in Steps 6-16:** The method effectively reallocates AP resources based on channel conditions, but it does not consider the overall network fairness. Fair AP Request, on the other hand, actively ensures that even UEs with poorer channel conditions are given priority during the fairness step (Steps 20-26), thereby leading to a more equitable distribution of network resources.
- **Step 19 of Adaptive AP Request:** The method increments the ServingAPs counter until the target number G is reached, focusing on immediate channel conditions without reassessing the overall network balance. Fair AP Request, however, revisits the AP assignments in its fairness step (Step 20), reallocating available AP resources to weaker UEs and ensuring a more uniform service distribution across the network.

Overall, the Fair AP Request method addresses the shortcomings of the Adaptive AP Request by not only optimizing for the best channel conditions but also by implementing mechanisms to ensure fairness and load balancing across the network. This results in improved overall network performance and user satisfaction, especially in high-density scenarios where effective resource management is crucial.

4.2.4 Baseline: All APs and Cellular

In this subsection, we discuss the baseline strategies, "All APs" and "Cellular," which serve as fundamental reference points for evaluating the performance of the AP selection methods. These baselines represent two extremes in the spectrum of network architectures, and comparing our proposed methods against them is crucial for understanding their relative strengths and weaknesses in Distributed Massive MIMO networks.

"All APs" is the unscalable approach of Distributed Massive MIMO, wherein each UE is simultaneously served by all available APs in the network. This approach assumes a fully connected network where there is no selection mechanism; every AP in the system contributes to serving every UE. While this approach might seem ideal in theory, offering the maximum possible diversity and potentially improving signal strength through constructive interference, it is far from practical. The "All APs" method leads to significant drawbacks, including:

- Excessive Overhead: With every AP involved in serving every UE, the coordination required between APs becomes increasingly complex and resource-intensive.
- High Energy Consumption: Since all APs are active for every UE, energy consumption is significantly higher than necessary.
- Increased Interference: The simultaneous transmission from multiple APs can cause interference, particularly in environments with a high density of UEs.

Despite these drawbacks, "All APs" serves as an important benchmark. It provides an upper bound on the potential performance of AP selection methods, helping us understand the maximum achievable performance in an idealized scenario.

On the other hand, "Cellular" represents the traditional approach to wireless network design, where each UE is exclusively served by a single AP, the one to which it is closest or has the best signal strength. This method is characteristic of conventional cellular networks, where the network is divided into cells, and each UE connects to the base station at the center of its cell. Moreover, the "Cellular" approach has limitations:

- Limited Flexibility: UEs are confined to a single AP, which can lead to suboptimal performance if the chosen AP is overloaded or if better channel conditions are available from other nearby APs.
- Lower Diversity Gains: Since each UE is served by only one AP, there is no opportunity to exploit diversity gains that could improve signal reliability and reduce fading.
- Potential for Bottlenecks: In dense deployment scenarios, certain APs may become overloaded, leading to increased latency and reduced data rates for UEs connected to those APs.

Despite these limitations, the "Cellular" method is a critical reference point because it represents the baseline performance of a traditional network. By comparing advanced AP selection methods to the "Cellular" baseline, we can assess how much performance improvement can be achieved through selection strategies.

Comparing the advanced AP selection methods developed in this thesis to the "All APs" and "Cellular" baselines is essential for several reasons:

1. Establishing a Performance Benchmark: The "All APs" baseline provides a theoretical upper limit of network performance, allowing us to gauge how close the advanced methods come to this ideal scenario.

2. Assessing Practicality: The "Cellular" baseline reflects the real-world constraints of current network architectures. By comparing advanced methods to this baseline, we can determine the practicality and real-world applicability of these methods.

3. Evaluating Trade-offs: Both baselines represent extreme approaches, with "All APs" maximizing diversity and "Cellular" maximizing simplicity. By comparing our methods against these extremes, we can better understand the trade-offs involved in terms of complexity, energy efficiency, and performance.

The baselines "All APs" and "Cellular" serve as crucial points of reference for evaluating the effectiveness of advanced AP selection methods in Distributed Massive MIMO networks. While "All APs" sets a theoretical performance ceiling, "Cellular" provides a practical comparison rooted in traditional network designs. Understanding how AP selection methods perform relative to these baselines helps to highlight their advantages, limitations, and overall potential for improving network efficiency and user experience.

4.3 ALGORITHM COMPLEXITY OF THE AP SELECTION METHODS

In distributed massive MIMO systems, the selection of APs plays a critical role in determining the algorithmic complexity. Complexity of an algorithm is the amount of resources (i.e. time or memory) required to perform a task or solve a specific problem [19]. The algorithm complexity behind each AP selection method can vary significantly based on the number of UEs K, the number of available APs L, and the size of the AP serving set G. This section formulates the algorithm complexity associated with each AP selection method: G APs, Dynamic AP Request, Adaptive AP Request, and Fair AP Request.

- "G APs": This method involves selecting the G nearest APs for each UE. For each UE, the method requires sorting the distances to all L APs, which has an algorithm complexity of $O(L \log L)$. After sorting, the nearest G APs are selected, and the UE is assigned to these APs. The total computational cost for all K UEs is therefore given by:

$$\mathrm{C} = K \cdot (L \log L + G) \tag{4.1}$$

- "Dynamic AP Request": In this method, each UE initially requests service from the nearest AP. The method involves sorting the distances to all L APs for each UE, resulting in an algorithm complexity of $O(L \log L)$. After sorting, each UE attempts to connect to the G closest APs that are not fully loaded. The total computational cost for all K UEs can be expressed as:

$$\mathrm{C} = K \cdot (L \log L + G) \tag{4.2}$$

- "Adaptive AP Request": This method involves a more complex decision-making process. Initially, the UE requests service from the nearest G APs. If the AP is fully loaded, the method evaluates the UE with the worst channel gain and may replace it if the new UE has a better channel gain. This process involves sorting the distances to L APs, similar to the previous methods, but also includes additional checks for channel gains, making it more computationally intensive. The computational cost is given by:

$$\mathrm{C} = K \cdot (L \log L + G \cdot \log K) \tag{4.3}$$

- "Fair AP Request": Our method is designed to optimize the allocation of APs by ensuring that each AP serves a fair number of UEs. This method initially uses a similar process as the Adaptive AP Request method to allocate the G nearest APs but then further refines the allocation by redistributing resources to the weakest UEs. This additional refinement adds to the computational cost, making it the most expensive in terms of computation. The total cost can be approximated by:

$$\mathrm{C} = K \cdot (L \log L + G \cdot \log K + K \log G) \tag{4.4}$$

The computational costs for each AP selection method are summarized in the following table 4.1:

AP Selection Method	**Computational Complexity**
G APs	$K \cdot (L \log L + G)$
Dynamic AP Request	$K \cdot (L \log L + G)$
Adaptive AP Request	$K \cdot (L \log L + G \cdot \log K)$
Fair AP Request	$K \cdot (L \log L + G \cdot \log K + K \log G)$

TABLE 4.1: Algorithm Complexity of AP Selection Methods

5

RESULTS

This chapter deals with the detailed analysis of the performance of various AP selection methods within distributed Massive MIMO networks. The network design and the challenges associated with it necessitate a thorough understanding of how AP selection methods can be optimized for peak performance. Our study is structured to solve these complexities, offering insights into the efficiency of these methods and their practical implications. In Section 5.1, we begin by outlining the methodology used for our simulations, highlighting the tools, setup, and parameters that form the foundation of our analysis. An overview of the evaluation process is provided, detailing the steps taken to assess the performance of AP selection methods under different scenarios and constraints. Section 5.2 sets the stage for a comparative analysis of the various AP selection methods, including a novel approach developed during this research, demonstrating their efficacy in typical network scenarios. Section 5.3 studies the trade-offs between performance gains and computational complexity, shedding light on the balance that must be struck to optimize resource usage in real-world applications. In Section 5.4, we then explore the influence of varying network conditions, such as user density and pilot sequence length, on the performance of AP selection methods. These examinations help to illustrate the resilience and adaptability of different methods in dynamic environments. Finally, Moreover, we conduct stress tests under extreme user densities to reveal the limitations and robustness of the AP selection methods, offering a comprehensive view of their performance under challenging conditions. The chapter concludes with a discussion of the results in Section 5.5, highlighting key findings and their implications for future network design and optimization.

5.1 METHODOLOGY

5.1.1 Simulation Environment

To conduct our analysis comprehensively, we utilized MATLAB to run 1000 Monte Carlo simulations. These simulations provide a robust statistical basis for our findings, allowing us to capture a wide range of potential network conditions and user distributions. Recognizing the computational intensity of these simulations, we incorporated parallelization into our MATLAB code. This optimization significantly reduced the computational time, allowing us to run extensive simulations more efficiently. The simulation was set up to reflect realistic network conditions, ensuring that our findings are applicable to real-world distributed massive MIMO networks. This includes considerations of various network parameters, such as the number of APs, user densities, and the different constraints that can impact performance. The network environment was set up with careful consideration of several critical factors, including the network topology, architecture, and user density. The topology was configured to represent a typical distributed massive MIMO setup, with uniform grid distributed APs strategically deployed to provide broad coverage. For the channel model and the SE model, we utilized the models introduced in Chapter 3. These models were selected to provide a detailed and accurate representation of the wireless communication environment, accounting for various factors such as path loss, fading, and interference. The SE model, in particular, was used to evaluate the system's ability to deliver high data rates under different network conditions and constraints. By combining these elements, a realistic network environment, an accurate channel and SE model, and extensive, optimized simulations, we ensured that our analysis is not only thorough but also directly applicable to the challenges faced by real-world distributed massive MIMO networks.

5.1.2 Overview of Evaluation Process

To frame our analysis, we established two baseline scenarios for reference. The first baseline scenario represents our upper bound, where each user in the network is served by all 64 APs. This scenario serves as a benchmark for the highest achievable performance. The second baseline scenario represents our lower bound, modeled after a traditional cellular network where each UE is served only by the nearest AP. This scenario provides a benchmark for the minimum expected performance.

Our thesis conducts a detailed comparative performance analysis of various AP selection methods across multiple potential scenarios. By evaluating these methods, we aim to identify how each one performs in terms of spectral efficiency. Beyond performance metrics, we also examine the system cost associated with each AP selection method. This analysis helps to demonstrate the trade-offs between performance and computational complexity, providing insights into the practical viability of each method. Moreover, we assume the network is static, as mobility introduces additional challenges like handovers and complex beam management, which are beyond the scope of this thesis.

Furthermore, our analysis adheres to the constraints outlined in Chapter 3, particularly that each AP can serve a maximum of τ_p UEs. By maintaining this constraint, we ensure that the network doesn't suffer from pilot contamination. This comprehensive approach allows us to offer a balanced assessment of each AP selection method, considering both their benefits and their resource requirements.

Table 5.1 summarizes the network configuration used in the simulations. The network area covers a 200 m $\times$ 200 m region with 64 APs arranged in a grid pattern, each positioned at a height of 5 meters. The UEs are randomly distributed according to a PPP, with the number of UEs varying between 25, 40, 64, and 200 to assess different network densities. The carrier frequency is set at 3.5 GHz, with maximum transmission powers of 200 mW for APs and 100 mW for UEs. The system operates with a channel bandwidth of 100 MHz and a noise figure of 9 dB. The coherence block length is 200 time slots, and the pilot sequence length is varied among 10,

Parameter	Value
Network area size	200 m $\times$ 200 m
AP distribution	grid
AP number, L	64 APs
AP height, h_{BS}	5 m
UE distribution	random PPP
UE Number, K	{25, 40, 64, 200}
Carrier frequency, f_c	3.5 GHz
Max AP power, $P_{AP_{max}}$	200 mW
Max UE power, $P_{UE_{max}}$	100 mW
Channel bandwidth, B	100 MHz
Noise figure, NF	9 dB
Coherence block length, τ_c	200
Pilot sequence length, τ_p	{10, 15, 20}

TABLE 5.1: Network configuration.

15, and 20 slots to evaluate the impact on network performance under different pilot contamination scenarios.

5.2 MOTIVATION AND INITIAL OBSERVATIONS

5.2.1 *Sufficiency of AP Selection*

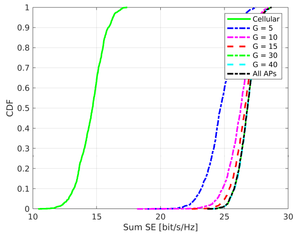
In this section, we aim to demonstrate the effectiveness and efficiency of AP selection methods. Unlike the scenario where each UE is served by all available APs, which leads to significant resource waste and increased system complexity, AP selection methods allocate a subset of APs to each UE. This approach not only conserves resources but also maintains high performance levels.

We will compare the performance of these AP selection methods against the baseline scenarios: the ideal case where each UE is served by all APs and the traditional cellular case where each UE is served by only one AP. Our objective is to show that AP selection methods can achieve near-peak performance for small AP serving set sizes while significantly reducing the system's resource consumption and complexity. This comparison will highlight the practical benefits of using AP selection methods in scalable distributed massive MIMO networks, which shows their potential to allow for scalability in distributed architectures.

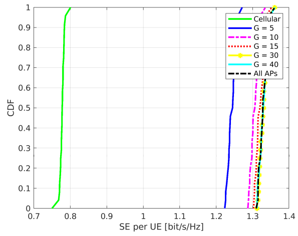
Figure 5.1 (a-d) illustrates the SE performance of various AP selection methods across different AP serving set sizes (G), compared to the two baseline scenarios: "All APs" and cellular. The analysis is based on the CDF of the SE of the network with a UE density of K = 25 UE and τ_p = 10. For each AP selection method, we analyze the Sum SE, SE per UE and 95% likely SE performance for different G values. Notably, for all AP selection methods except "Fair AP Request" we observe that performance consistently improves as G increases. When G reaches 10, the performance closely approaches that of the upper bound, represented by the "All APs" scenario. Additionally, across all AP selection methods, there is a significant enhancement in performance (approximately 60% better) compared to the cellular scenario. This demonstrates the effectiveness of using a subset of APs to achieve near-peak performance, highlighting the advantages of AP selection methods in optimizing network efficiency. The increase in SE with larger G values is due to the greater diversity and spatial resources available when more APs are involved in serving the UEs. As G grows, more APs contribute to the signal quality, increasing the overall spectral efficiency. The convergence towards the 'All APs' scenario at G = 10 suggests that involving more than 10 APs per UE does not significantly improve performance. This is because the additional APs are farther away, resulting in weaker signals. Consequently, the desired signal strength is lower, leading to a reduced SINR, which in turn diminishes throughput and spectral efficiency.

The "Fair AP Request" method exhibits consistent performance across different G values, achieving peak performance regardless of the initial AP serving set size. This is because this method initially allocates APs based on the given G value and subsequently redistributes any unallocated APs to the UEs with the weakest channels, effectively maximizing resource utilization and ensuring that even the weakest UEs receive sufficient support. This redistribution leads to peak Sum SE performance even with smaller G values.

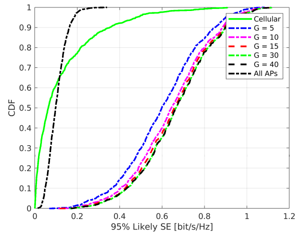
As a result of our observations in Figure 5.1, we assume for our subsequent analysis a value of G = 10 for "G APs", "Dynamic AP Request" and "Adaptive AP Request". For "Fair AP Request" we assume a value of G = 5, since "Fair AP Request" already achieves peak performance with this value.



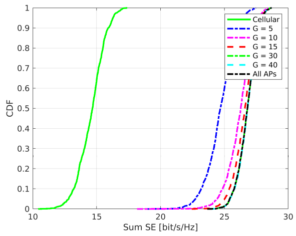
(a) G APs - Sum SE



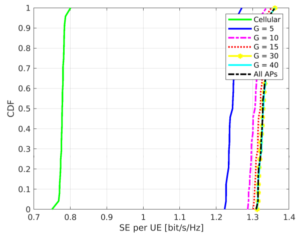
(b) G APs - SE per UE



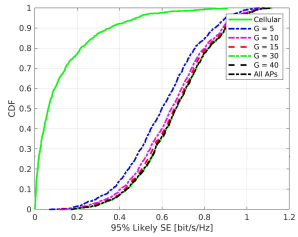
(c) G APs - 95% Likely SE



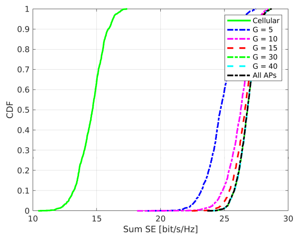
(d) Dynamic AP Request - Sum SE



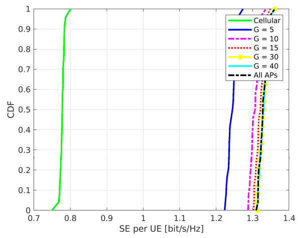
(e) Dynamic AP Request - SE per UE



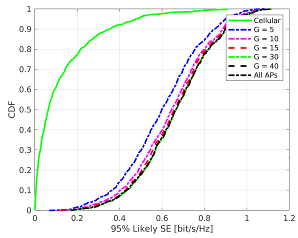
(f) Dynamic AP Request - 95% Likely SE



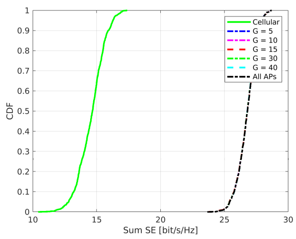
(g) Adaptive AP Request - Sum SE



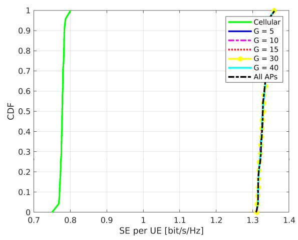
(h) Adaptive AP Request - SE per UE



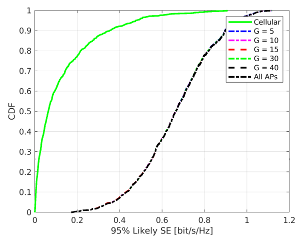
(i) Adaptive AP Request - 95% Likely SE



(j) Fair AP Request - Sum SE



(k) Fair AP Request - SE per UE



(l) Fair AP Request - 95% Likely SE

FIGURE 5.1: SE performance of different AP Selection Methods for different G values - K = 25 UEs, $\tau_p = 10$.

5.2.2 *Comparative Analysis of AP Selection Methods*

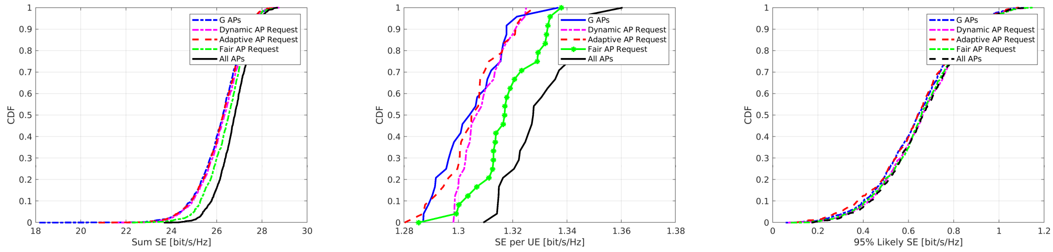
In this section, we conduct a comparative analysis of the different AP selection methods to evaluate their performance under usual network conditions. By comparing the Sum SE, average SE, and 95% likely SE performance metrics, the analysis will help us to understand how these methods perform relative to the upper bound "All APs" and why certain methods, like Fair AP Request, consistently outperform others. Through this comparison, we will highlight the efficiency of each AP selection method, providing valuable insights for optimizing distributed Massive MIMO networks. It is important to note that we are looking at the constrained AP selection. This means that each AP can serve a maximum of K = τ_p UEs in order to avoid pilot contamination, as we have already explained in Chapter 3.

Figure 5.2 shows the Sum SE, SE per UE and 95% likely SE performance of various AP selection methods with UE = 25, G = 10 (G = 5 for Fair AP Request), and τ_p = 10. For comparison, we use "All APs" as the upper bound, omitting the lower bound "cellular" scenario to avoid scaling issues and because we've already established that all AP selection methods significantly outperform the cellular scenario.

Especially in Sum SE and SE per UE, we can see that the Fair AP Request method outperforms the others, nearly matching the performance of the upper bound in Sum SE. The other AP selection methods show similar performance levels to each other. This superior performance of the Fair AP Request method is due to its superior design which maximizes the resource utilization, i.e., allocated all underutilized APs to weak UEs in the network compared to the other methods. A similar trend is observed in SE per UE. The Fair AP Request method continues to lead, demonstrating its advantage in SE performance.

In 95% likely SE, we notice that all AP selection methods, including the "Fair AP Request", perform almost identically and close to the upper bound. This indicates that under typical network conditions, all the methods achieve nearly optimal performance, with the Fair AP Request method maintaining a slight edge. This once again has to do with the fair design of this method, where all possible remaining resources after the initial UE-AP allocation are assigned to the weakest UEs.

In the upcoming sections, we will dive deeper into the network performance of various AP selection methods across a range of scenarios and conditions. We will explore how these methods hold up under higher UE densities and varying pilot sequence lengths, revealing insights into their robustness and adaptability in more demanding environments. But first let's take a look at the computational cost of the different AP selection methods in Section 5.3.



(a) Sum SE (b) SE per UE (c) 95% Likely SE

FIGURE 5.2: SE Performance of AP Selection Methods for UE = 25, G = 10 (G = 5 for Fair AP Request), τ_p = 10.

5.3 ALGORITHM COMPLEXITY ANALYSIS

In this section, we perform a detailed analysis of the algorithm complexity associated with the different AP selection methods introduced earlier. We evaluate the algorithm complexity of each method, defined as the ratio of algorithm cost to the median SE achieved by each method. This approach allows us to compare the relative merits of each method. For clarity, the summary table of the algorithm costs of each AP selection method is presented again in Table 4.1.

AP Selection Method	**Computational Cost**
G APs	$K \cdot (L \log L + G)$
Dynamic AP Request	$K \cdot (L \log L + G)$
Adaptive AP Request	$K \cdot (L \log L + G \cdot \log K)$
Fair AP Request	$K \cdot (L \log L + G \cdot \log K + K \log G)$

TABLE 5.2: Algorithm Cost of AP Selection Methods

We now perform a comparative analysis of the computational efficiency for a system with $K = 25$ UEs, $L = 64$ APs, and an AP serving set size $G = 10$ (except for Fair AP Request, where $G = 5$). The efficiency is calculated as eff $= \frac{C}{SE_m}$, where C is the computational cost and SE_m is the median spectral efficiency achieved by each method. **For the "G APs" method:**

$$\text{C} = 25 \cdot (64 \log 64 + 10) = 9850 \text{ Operations} \tag{5.1}$$

With a median SE of $SE_m = 1.30$ bit/s/Hz, the efficiency is:

$$\text{eff} = \frac{9850}{1.30} \approx 75.77\% \tag{5.2}$$

For the "Dynamic AP Request" method:

$$\text{C} = 25 \cdot (64 \log 64 + 10) = 9850 \text{ Operations} \tag{5.3}$$

With a median SE of $SE_m = 1.30$ bit/s/Hz, the efficiency is identical to G APs:

$$\text{eff} = \frac{9850}{1.30} \approx 75.77\% \tag{5.4}$$

For the "Adaptive AP Request" method:

$$\text{C} = 25 \cdot (64 \log 64 + 10 \cdot \log 25) = 10760 \text{ Operations} \tag{5.5}$$

With a median SE of $SE_m = 1.305$ bit/s/Hz, the efficiency is:

$$\text{eff} = \frac{10760}{1.305} \approx 82.44\% \tag{5.6}$$

For the "Fair AP Request" method, where $G = 5$:

$$\text{C} = 25 \cdot (64 \log 64 + 5 \cdot \log 25 + 25 \log 5) = 11630 \text{ Operations} \tag{5.7}$$

With a median SE of $SE_m = 1.385$ bit/s/Hz, the efficiency is:

$$\text{eff} = \frac{11630}{1.385} \approx 83.95\% \tag{5.8}$$

The Fair AP Request method has an algorithm cost approximately 18% higher than the G APs method ($\frac{11630-9850}{9850} \times 100 \approx 18\%$ more). However, it achieves a median SE that is 6.54% higher ($\frac{1.385-1.30}{1.30} \times 100 \approx 6.54\%$ more). The efficiency of the Fair AP Request method is therefore justified by the significant improvement in SE, making it the better option despite the increased computational cost. Similarly, compared to Dynamic AP Request, Fair AP Request incurs an 18% higher computational cost. The SE improvement remains 6.54%, making Fair AP Request more efficient. The Adaptive AP Request method has a 10.44% lower computational cost than Fair AP Request ($\frac{11630-10760}{10760} \times 100 \approx 8.1\%$ more). However, the Fair AP Request achieves a 6.13% higher SE ($\frac{1.385-1.305}{1.305} \times 100 \approx 6.13\%$ more), which justifies its use.

In summary, while the Fair AP Request method incurs a slightly higher algorithm cost, its superior median SE results in the highest efficiency among the evaluated methods. This makes it the optimal choice, especially in scenarios where achieving higher spectral efficiency is critical, even at the expense of minimally increased algorithm cost. The trade-off between cost and performance is well-balanced, affirming the Fair AP Request method's value in distributed massive MIMO systems.

5.4 INFLUENCE OF NETWORK CONDITIONS

In this section, we look at various network conditions that impact the performance of different AP selection methods within a distributed Massive MIMO network. The most important conditions we focus on are UE density and pilot sequence length, which both play critical roles to evaluate the efficiency of the different AP selection methods.

Understanding the influence of network conditions is crucial for optimizing network performance and ensuring reliable communication, particularly in dynamic and high-demand environments where we have limited resources. High UE densities can lead to increased interference and competition for the limited network resources, which affects the capability of AP selection methods to maintain high performance. Moreover, pilot sequence length affects the accuracy of channel estimation, which is critical in effective AP selection and overall network performance.

In this section, we firstly investigate the effect of pilot sequence length, exploring its implications on the resulting network performance. Next, we analyze the impact of UE density on the performance of various AP selection methods, providing insights into how these methods scale with increasing numbers of users. By examining these factors, we aim to highlight the robustness and adaptability of different AP selection strategies under varying network conditions, ultimately contributing to the development of more efficient and scalable distributed Massive MIMO systems.

5.4.1 *Impact of Pilot Sequence Length*

One of the most important parameters to study is the length of the pilot sequence. There are certain scenarios where it makes sense to sacrifice a part of the data transmission phase in order to increase the length of the pilot phase or the pilot sequence. In massive MIMO systems where we have a very large number of antennas, the base station needs more accurate CSI to perform effective beamforming and spatial multiplexing. Longer pilot sequences can provide more accurate CSI, which is crucial for maintaining system performance. For applications requiring stringent QoS, longer pilot sequences ensure more accurate channel estimation, which is essential for maintaining the required performance levels. Short pilot sequences reduce the overhead, potentially increasing spectral efficiency. However, channel estimation accuracy is decreased, leading to poorer performance in scenarios with high interference or user density [14].

Let's take a look at Figure 5.3. In this figure, we compare the Sum SE performance of the AP selection methods for increasing lengths of the pilot sequence for a UE density K = 25 UE and G = 10. With longer pilot sequences, the all methods exhibit a reduction of about 12% in spectral efficiency due to increased overhead. The longer pilot sequences occupy more of the limited coherence interval, leaving less time for data transmission, which directly impacts the overall system throughput.

Despite this general slight decline in performance, the "Fair AP Request" method demonstrates a remarkable resilience compared to the other AP selection methods. As the pilot sequence length increases, the SE performance of the "Fair AP Request" method steadily converges towards that of the "All APs" approach, while significantly outpacing the other AP selection strategies. This trend highlights the exceptional resilience of the "Fair AP Request" method, especially in challenging scenarios where pilot contamination becomes a critical concern. The underlying reason for this superior performance lies in how pilot contamination limits each AP to serving only $X = \tau_p$ UEs. By reallocating the remaining resources of underutilized APs after the initial AP-

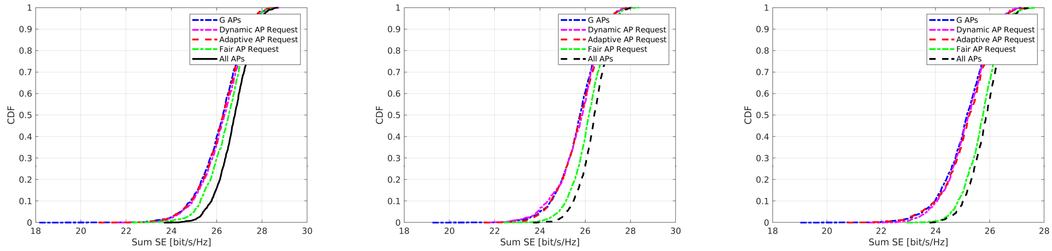
UE allocation process, the "Fair AP Request" method directs those resources to support the weakest UEs, thus fully exploiting the available AP capacity of the network.

The superior performance of "Fair AP Request" in the context of longer pilot sequences can be explained by its design, which carefully balances load and optimizes the selection of APs based on the channel conditions of UEs. By prioritizing fairness and ensuring that even the weakest UEs are served by APs with the best available channel conditions, "Fair AP Request" effectively mitigates the negative impacts of pilot contamination. This allows it to maintain a higher level of SE even as the conditions for accurate channel estimation deteriorate.

In contrast, the other methods fall short of the performance achieved by the "Fair AP Request" method due to a fundamental difference in resource allocation, especially with longer pilot sequences. Unlike "Fair AP Request", these methods do not make use of the remaining available pilots after the initial AP assignments. As a result, significant network resources remain underutilized, leading to suboptimal overall performance. The "Fair AP Request" method, by contrast, strategically reallocates these unused resources to ensure that even the weakest UEs are supported, maximizing network efficiency and enhancing spectral efficiency across the board. This comprehensive utilization of available resources is what gives "Fair AP Request" its edge over the other methods.

These findings highlight the critical importance of selecting an appropriate AP selection method in distributed massive MIMO networks, particularly in environments where pilot contamination is a significant concern. The ability of "Fair AP Request" to maintain superior performance under challenging conditions makes it an attractive option for network deployments that must contend with varying pilot sequence lengths and high UE densities. As we delve deeper into the analysis, it becomes clear that the choice of AP selection method can significantly influence the overall network performance, especially in terms of spectral efficiency and resilience to pilot contamination.

Due to space constraints, you'll find the detailed results for SE per UE and the 95% likely SE included in the Appendix A in Figure A.1 and Figure A.2 respectively. Furthermore, since all AP selection methods perform better for $\tau_p = 10$, we will continue with this value for the pilot sequence length in subsequent analysis in this chapter.



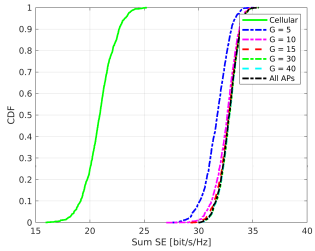
(a) $\tau_p = 10$ (b) $\tau_p = 15$ (c) $\tau_p = 20$

FIGURE 5.3: The Sum SE performance of AP Selection Methods for UE = 25, G = 10 (G = 5 for Fair AP Request) with different τ_p values.

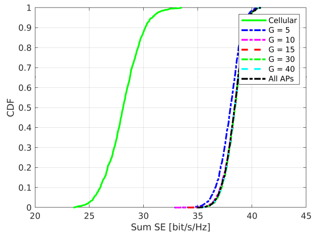
5.4.2 Impact of UE Density

Now let's investigate how the density of UE affects the performance of AP selection methods in a distributed Massive MIMO network. UE density is a critical factor in network design, as it directly influences interference levels, resource allocation, and overall network performance. In this analysis, we will compare the performance of various AP selection methods across different UE densities to observe the changes in spectral efficiency and overall network performance. This comparison will provide valuable insights into which AP selection methods are most effective in densely populated environments and how they can be optimized to maintain high performance under such conditions.

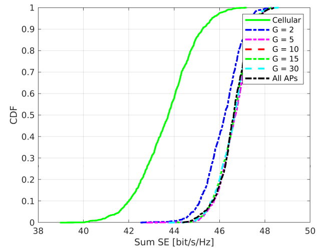
Firstly, let's take a look at Figure 5.4 (a-d), which illustrates the impact of the UE density on the selection of G for the different AP selection methods with $\tau_p = 10$. We can see that for higher UE densities, increasing G does not significantly improve performance. This is because, with more users, the inter-UE interference between their signals increases, which negatively impacts performance. Therefore, the benefits of using a larger G diminish as UE density rises. This highlights the need to manage inter-UE interference carefully, especially in dense network environments. Due to space constraints, you'll find the detailed results for SE per UE and the 95% likely SE included in the Appendix A in Figure A.3 and Figure A.4 respectively.



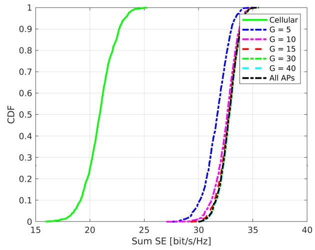
(a) G APs
UE = 40



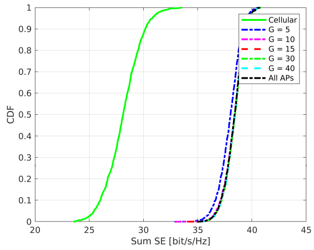
(b) G APs
UE = 64



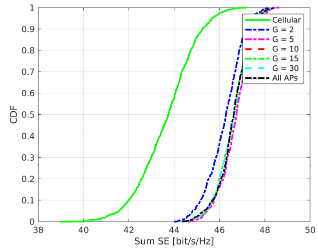
(c) G APs
UE = 200



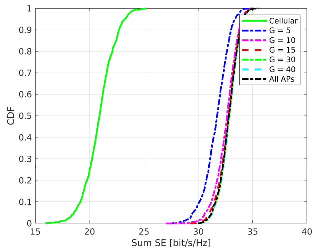
(d) Dynamic AP Request
UE = 40



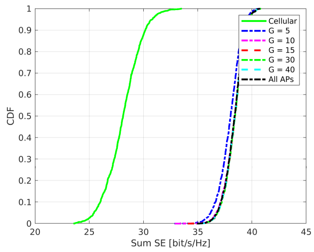
(e) Dynamic AP Request
UE = 64



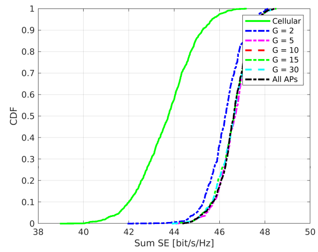
(f) Dynamic AP Request
UE = 200



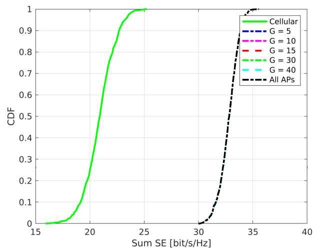
(g) Adaptive AP Request
UE = 40



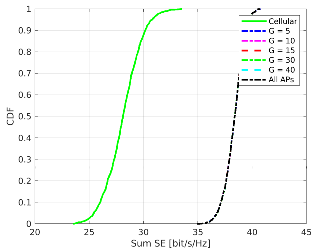
(h) Adaptive AP Request
UE = 64



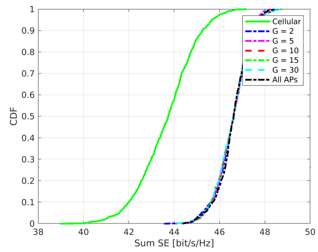
(i) Adaptive AP Request
UE = 200



(j) Fair AP Request
UE = 40



(k) Fair AP Request
UE = 64



(l) Fair AP Request
UE = 200

FIGURE 5.4: Sum SE performance of different AP Selection Methods for different G values and for increasing UE Densities - $\tau_p = 10$.

Now let's take a look at Figure 5.5, where we analyze the Sum SE performance of various AP selection methods under different UE densities (40, 64, 200), with a fixed pilot sequence length $\tau_p = 10$ and G = 10. This analysis provides valuable insights into how increasing UE density affects the performance of these methods, revealing both their strengths and limitations in high-density environments.

As the UE density increases, both the "G APs" and "Dynamic AP Request" methods exhibit a noticeable decline in Sum SE performance. This decline is particularly pronounced at higher densities, such as K=200 UEs. The primary reason for this performance drop lies in the inherent limitations of these methods in managing high UE loads.

In the "G APs" method, each UE is connected to a fixed number of the nearest APs, without considering the overall network load or the inter-UE interference caused by neighboring UEs. As the number of UEs increases, this static approach leads to significant inter-UE interference among UEs sharing the same APs, thus degrading the SE. Similarly, the "Dynamic AP Request" method, while more flexible than "G APs," still struggles under high UE densities because it does not adequately address the dynamic load balancing needed to mitigate interference and optimize resource allocation in such scenarios.

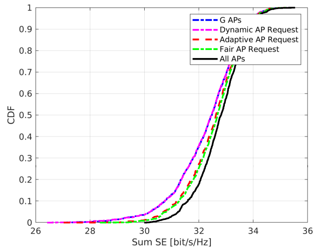
In contrast to those methods, both "Adaptive AP Request" and "Fair AP Request" demonstrate remarkable resilience to increasing UE densities. As the number of UEs rises, these methods maintain a Sum SE performance nearly on par with the "All APs" baseline. However, it is important to mention, that the Fair AP Request method requires a smaller G value for the initial UE-AP allocation, which makes it faster and computationally less demanding.

The key to the success lies of Fair AP Request in its ability to adapt to the network's challenging conditions. Fair AP Request, prioritizes fairness, ensuring that weaker UEs are still served optimally. This dual focus on load balancing and fairness allows it to sustain high SE levels, even as the network becomes increasingly congested.

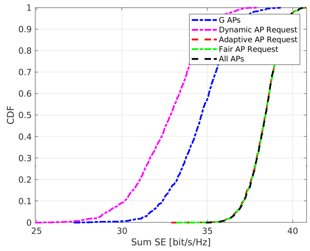
At the extreme density of K=200 UEs, we effectively stress-test the AP selection methods, pushing the network to its limits. Under these conditions, all methods, including "All APs," struggle to maintain high SE due to severe interference and the limited availability of resources. The high UE density exacerbates the competition for resources, leading to significant degradation in SE across the board.

This scenario underscores the need for advanced scheduling strategies in distributed massive MIMO networks. When UE density reaches such high levels, merely relying on AP selection methods is insufficient to manage the resulting interference and resource constraints. Effective scheduling of UEs becomes critical to ensure that network performance remains within acceptable bounds. By strategically timing the service of UEs and optimizing resource allocation, scheduling can help alleviate the stress on the network and improve the overall SE, even in extremely dense environments.

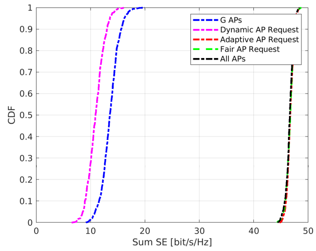
Due to space constraints, you'll find the detailed results for SE per UE and the 95% likely SE included in the Appendix A in Figure A.5 and Figure A.6 respectively.



(a) UE = 40



(b) UE = 64



(c) UE = 200

FIGURE 5.5: The Sum SE Performance of AP Selection Methods for different UE densities with τ_p = 10 and G = 10 (G = 5 for Fair AP Request).

5.5 RESULTS DISCUSSION: IMPLICATIONS ON NETWORK DESIGN

Our findings provide a comprehensive understanding of how different AP selection methods perform under various network conditions, including varying pilot sequence lengths, UE densities, and stress testing scenarios. These results are significant for the design and optimization of distributed massive MIMO networks, particularly in balancing performance, scalability, and resource management.

One of the key insights from our study is that the "Fair AP Request" method significantly outperforms all other methods under typical network conditions, such as low UE density. This superior performance is primarily due to its design, which allocates all underutilized APs to the weakest UEs, ensuring that even the UEs with the poorest channel conditions receive sufficient resources. In contrast, other methods like "G APs" and "Dynamic AP Request" do not prioritize this redistribution of resources, leading to suboptimal performance in comparison.

The results further demonstrate that the "G APs" and "Dynamic AP Request" methods tend to fail under challenging network conditions, such as high UE densities and extended pilot sequences. Their performance significantly degrades due to their inability to dynamically balance the load across the network. This underscores the necessity of employing more advanced methods, such as "Adaptive AP Request" and "Fair AP Request," which have shown resilience and superior performance even in demanding scenarios. Among these, the "Fair AP Request" method stands out, not only for its ability to maintain high performance for weaker UEs but also for its computational efficiency, making it the optimal choice for environments with high user densities or limited network resources.

Additionally, the analysis of pilot sequence length reveals a trade-off between pilot overhead and SE performance. While longer pilot sequences are necessary to mitigate pilot contamination and improve channel estimation accuracy, they reduce effective data transmission time, leading to lower SE across all methods. However, the "Fair AP Request" method shows a remarkable ability to mitigate this trade-off, maintaining performance close to the "All APs" baseline even as pilot sequence length increases. This suggests that in scenarios requiring extended pilot sequences, using a robust

AP selection method like "Fair AP Request" can help sustain high SE while ensuring accurate channel estimation.

Stress testing at extreme UE densities (e.g., $K = 200$) highlights the scalability challenges faced by distributed massive MIMO networks. Even the most advanced AP selection methods struggle under such conditions, primarily due to increased interference and limited resources. This scenario emphasizes the need for additional mechanisms, such as scheduling, where not all UEs are served simultaneously but rather in subsets at each time stamp. Scheduling can distribute the load more evenly across time, reducing the instantaneous demand on network resources and mitigating interference, thus playing a crucial role in sustaining performance in dense urban areas or large-scale IoT deployments.

Lastly, the superior performance of the "Fair AP Request" method, especially in high-density scenarios, underscores the importance of fairness and load balancing in network design. By ensuring that even the weakest UEs are allocated sufficient resources, this method not only improves overall network performance but also enhances user experience, particularly for those in less favorable conditions. Designing networks with fairness as a core principle can lead to more equitable service distribution, reducing disparities between users and ensuring a more consistent quality of service, which is particularly important in heterogeneous environments with varying channel conditions.

6

Conclusion and Future Work

This thesis systematically explored the performance of various AP selection methods in distributed massive MIMO networks under diverse conditions. The results highlight the critical role of advanced AP selection strategies, particularly our "Fair AP Request" method, which significantly outperforms others, even in low UE density scenarios. This superior performance is due to its design that reallocates underutilized APs to the weakest UEs, ensuring those with poor channel conditions receive sufficient resources. In contrast, simpler methods like "G APs" and "Dynamic AP Request" performed adequately under less demanding conditions but faltered as UE density increased and pilot sequence lengths extended. The "Fair AP Request" method consistently maintained spectral efficiency close to the "All APs" baseline, even in challenging scenarios with limited APs and high UE density. This study also emphasized the impact of pilot sequence length on network performance, demonstrating how different AP selection methods respond to longer pilot sequences. Overall, the research contributes valuable insights into designing scalable distributed massive MIMO networks, particularly in managing load and interference in dense environments.

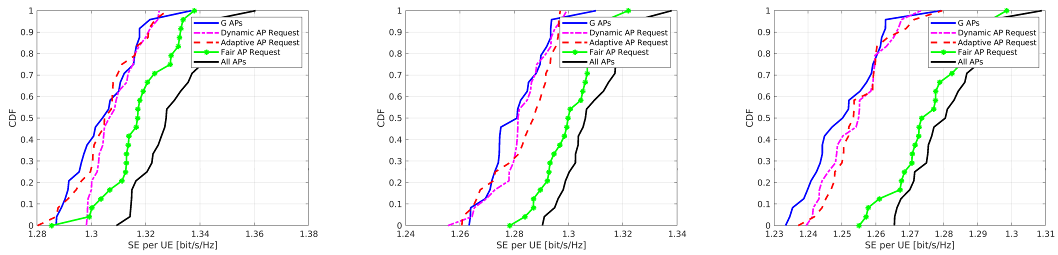
However, this study has limitations. The system model, while effective for comparing AP selection methods, does not fully capture the complexities of real-world networks, such as mobility, dynamic channel conditions, and varying traffic loads. Additionally, fixed parameters, like the number of APs and pilot sequence length, limit the generalizability of the findings. The focus on spectral efficiency as the primary metric also leaves other important aspects, such as energy efficiency and latency, less explored.

Future research could address these limitations by enhancing the "Fair AP Request" method with adaptive algorithms that respond to real-time network conditions and by incorporating machine learning techniques to improve AP selection efficiency. Expanding the system model to include user mobility, variable traffic loads, and energy efficiency would offer a more accurate representation of real-world networks and lead to more robust AP selection strategies.

The scalability challenges identified in this study also underscore the need for effective scheduling mechanisms. By serving subsets of UEs at different time stamps, scheduling could help manage high-density environments more effectively, reduce inter-UE interference, and ensure adequate service for all users. Future work should explore integrating scheduling with advanced AP selection methods to achieve greater network efficiency, especially as the number of UEs and interference levels increase.

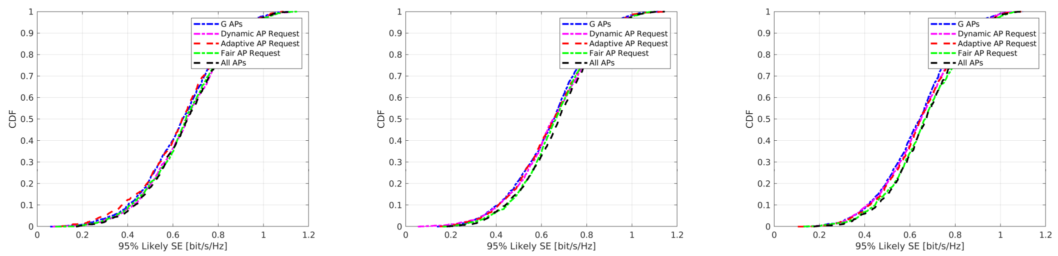
A

Appendix



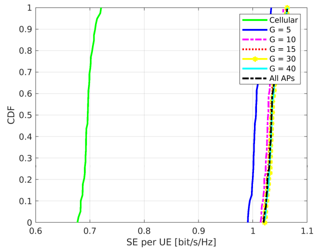
(a) $\tau_p = 10$ (b) $\tau_p = 15$ (c) $\tau_p = 20$

FIGURE A.1: The SE per UE performance of AP Selection Methods for UE = 25, G = 10 (G = 5 for Fair AP Request) with different τ_p values.

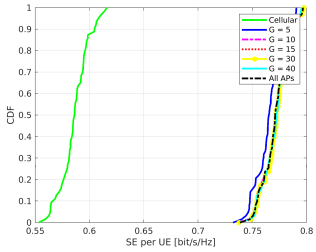


(a) $\tau_p = 10$ (b) $\tau_p = 15$ (c) $\tau_p = 20$

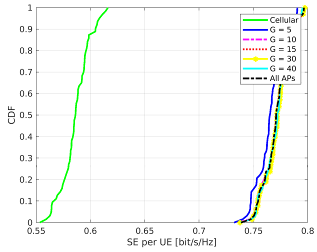
FIGURE A.2: The 95% Likely SE performance of AP Selection Methods for UE = 25, G = 10 (G = 5 for Fair AP Request) with different τ_p values.



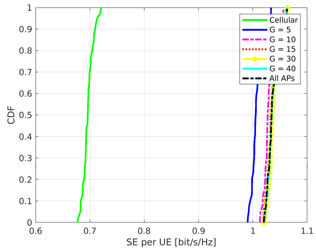
(a) G APs
UE = 40



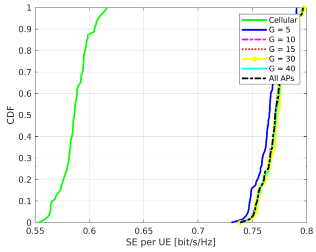
(b) G APs
UE = 64



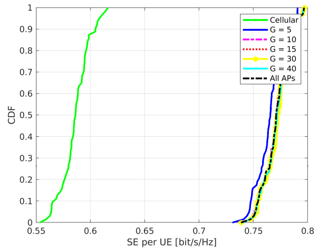
(c) G APs
UE = 200



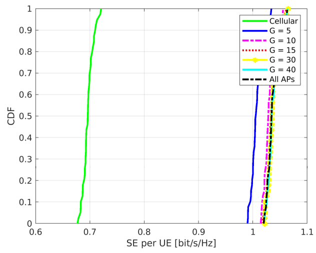
(d) Dynamic AP Request
UE = 40



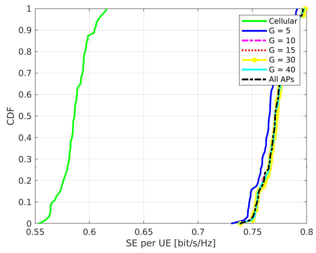
(e) Dynamic AP Request
UE = 64



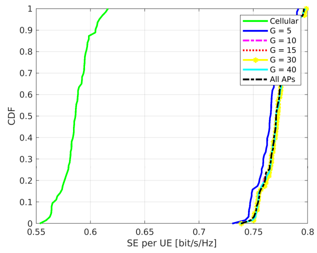
(f) Dynamic AP Request
UE = 200



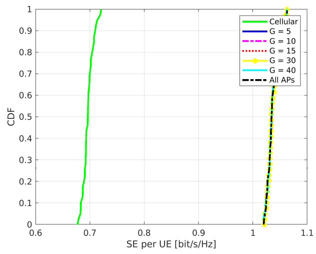
(g) Adaptive AP Request
UE = 40



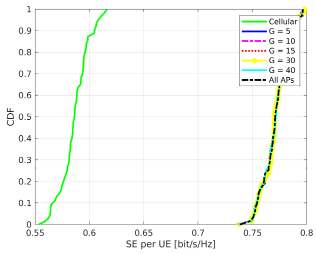
(h) Adaptive AP Request
UE = 64



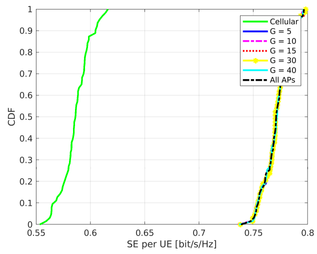
(i) Adaptive AP Request
UE = 200



(j) Fair AP Request
UE = 40

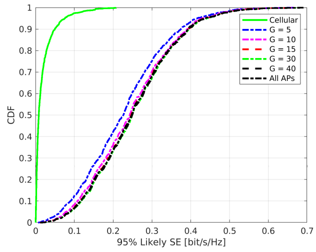


(k) Fair AP Request
UE = 64

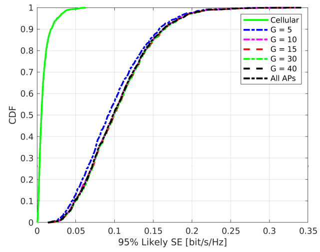


(l) Fair AP Request
UE = 200

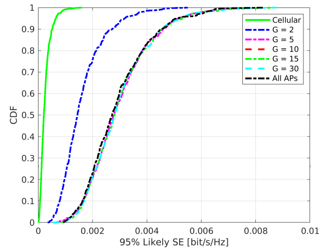
FIGURE A.3: SE per UE performance of different AP Selection Methods for different G values and for increasing UE Densities - $\tau_p = 10$.



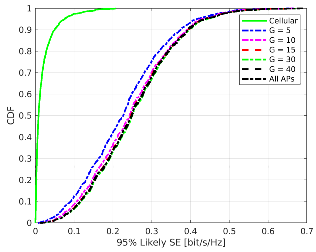
(a) G APs
UE = 40



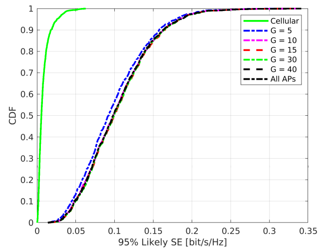
(b) G APs
UE = 64



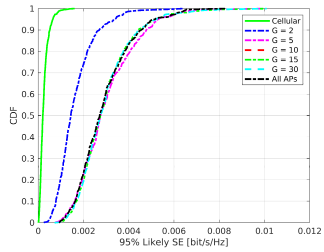
(c) G APs
UE = 200



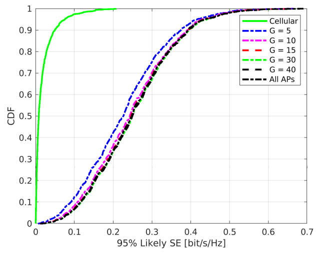
(d) Dynamic AP Request
UE = 40



(e) Dynamic AP Request
UE = 64



(f) Dynamic AP Request
UE = 200



(g) Adaptive AP Request
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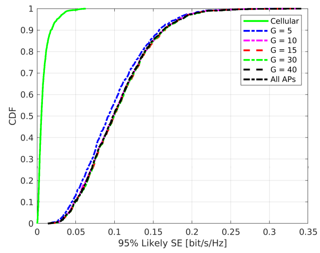
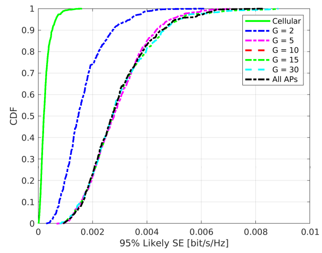
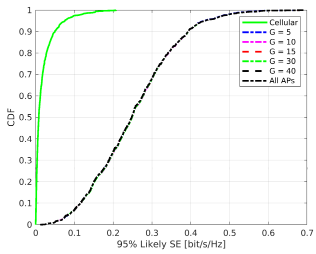


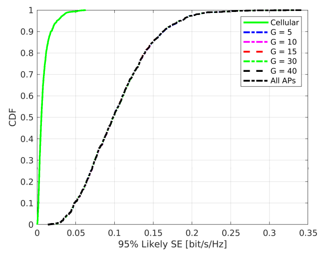
(h) Adaptive AP Request
UE = 64



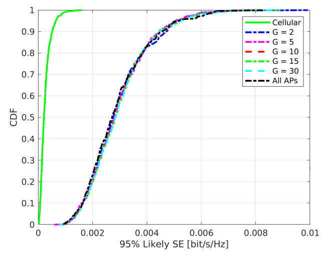
(i) Adaptive AP Request
UE = 200



(j) Fair AP Request
UE = 40

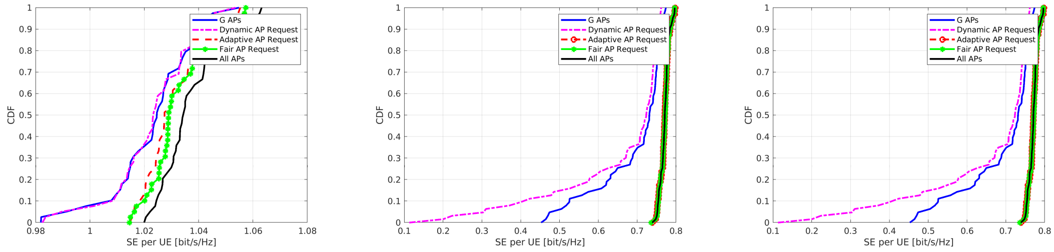


(k) Fair AP Request
UE = 64



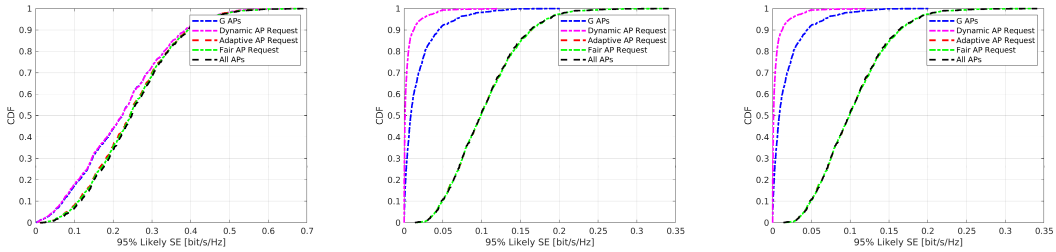
(l) Fair AP Request
UE = 200

FIGURE A.4: 95% Likely SE performance of different AP Selection Methods for different G values and for increasing UE Densities - $\tau_p = 10$.



(a) UE = 40 (b) UE = 64 (c) UE = 200

FIGURE A.5: The SE per UE Performance of AP Selection Methods for different UE densities with τ_p = 10 and G = 10 (G = 5 for Fair AP Request).



(a) UE = 40 (b) UE = 64 (c) UE = 200

FIGURE A.6: 95% Likely SE Performance of AP Selection Methods for different UE densities with τ_p = 10 and G = 10 (G = 5 for Fair AP Request).

B

ABBREVIATIONS

MIMO Multiple-Input Multiple-Output

APs Access Points

UE User Equipment

UEs User Equipments

SINR Signal-to-Interference-plus-Noise Ratio

SE Spectral Efficiency

PPP Poisson Point Process

TDD Time Division Duplexing

CPU Central Processing Unit

IoT Internet of Things

BS Base Station

BSs Base Stations

CSI Channel State Information

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