Channel Estimation and Active User Detection in 5G and Beyond for Massive MIMO Communication Systems

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DEDICATED TO

All those who believed in me, inspired me, and made this journey possible.

CERTIFICATE OF APPROVAL

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ABSTRACT

The Massive Multiple Input Multiple Output (MIMO) technology has revolutionized the way we manage multiple data streams in parallel for improved energy and spectral efficiency in the area of advanced wireless communication. Massive MIMO technology is very effective for handling the task of channel estimation (CE) and active user detection (AUD), specifically in situations where there are many users and only a small percentage of them are sending or receiving data during a given time frame. However, there exist some grave challenges to accurately estimate the channels associated with multiple transmitters and receivers, and identifying the active users. Experimental analysis has validated that the user activity patterns exhibit sparsity in spatial, temporal, and angular domains. Such sparsity patterns can be exploited using Compressed Sensing (CS) techniques to handle such challenges. A novel strategy is proposed in this research, which utilizes an optimized pilot design based in CS framework inside a one-ring channel model. In this approach, primarily the users are clustered into compact circular sub-groups based on the user's distance and angle towards transmitter. This model improves the accuracy of CE by assigning pilot sequences among antenna groups more efficiently at Base Station (BS). That is to say that instead of assigning unique pilot sequence to each antenna, the pilot sequence is assigned to antennas in groups. Particularly, spatial, and angular sparsity in Massive MIMO system, are explored and it has been observed that users scatter differently according to their distance and height from the BS. Secondly, the minimal angular spread among users, significantly facilitates with the process of identifying the active users after classifying the users in circular clusters based on their spatial signatures. The proposed method based on combination of spatial and angular sparsity further integrated with a modified form of Orthogonal Matching Pursuit (OMP) algorithm to estimate the limited channels. The major disadvantage of conventional CS algorithm is that it needs prior knowledge of sparsity, whereas the experimental results show that knowing the accurate sparsity level is not available in advance. Moreover, Massive MIMO systems face the challenge of acquiring accurate channel state information (CSI) due to the large number of antennas and the high-dimensional nature of the system.

These challenges are addressed by the proposed enhanced OMP (OMPe) algorithm, that is designed to adaptively determine the sparsity level. Thirdly, security and malicious access during the estimation process is also a major concern in emerging communication systems. To address this concern, Logistic Map Chaotic Sequence is integrated in the pilot design, securing the end-to-end transmission. Simulations have been performed to assess and benchmark the proposed Massive MIMO scenario, model, and OMPe. The findings demonstrate that the proposed Massive MIMO model improves the system efficiency and reduce the high pilot overhead, and the OMPe is more efficient as compare to conventional OMP and OMP with Iterative Refinement (OMP-IR) algorithms. The results further illustrate that the CS based AUD method has optimized the distribution of resources and improve the system performance of massive MIMO technology. For the task of channel estimation, comparative visualization of OMPe with available versions, OMP and OMP-IR show that OMPe outperforms in AUD precision, increasing the reliability of the system. Finally, this research has addressed the critical challenges of CE, high pilot overhead and AUD in Massive MIMO scenario and offers insightful solutions for improving the performance, and potentially provide major breakthroughs for future generations of wireless communication.

List of Publications and Submissions

[1]. **Ubaid Umar**, Athar Waseem, Aqdas Naveed. "Robust User Identification in Massive MIMO Systems Using Compressed Sensing Techniques", *in Journal of Electrical and Computer Engineering*, 2025, 2784608, 13 pages, 2025. https://doi.org/10.1155/jece/2784608 ***(Published)***.

[2]. **Ubaid Umar**, Athar Waseem, Aqdas Naveed, Fahad Munir, Mardeni Roslee and Sara Ayub. 2024. "Active User Detection in Massive MIMO Systems Using Compressed Sensing" in *10th International Conference on Engineering and Emerging Technologies (ICEET 2024)* ***(Published)***.

[3]. **Ubaid Umar**, Athar Waseem, Aqdas Naveed, Fahad Munir, Sara Ayub, Muhammad Irfan and Mardeni Roslee. 2025. "Powering the 6G and Beyond Wireless Era: AI and Deep Learning Innovations" in *11th International Conference on Engineering and Emerging Technologies (ICEET 2025)* ***(Published)***.

[4]. Muhammad Irfan, Athar Waseem, Mardeni Roslee, **Ubaid Umar**, Irum Nosheen and Fahad Munir. 2023. "Security Threats and Mitigation Approaches for D2D Communication in 5G & B5G Wireless Networks" in *International Conference on Electrical, Communication and Computer Engineering (ICECCE)* ***(Published)***.

[5]. Khalid Ibrahim, Sadiq Ahmed, **Ubaid Umar**, Athar Waseem, Soon Xin Ng and Adqas Naveed Malik. 2023. "Mitigating Rate-Aware Jamming Attacks: A Deceptive Anti-Jamming Approach with Enhanced Utility" in *International Conference on Engineering and Emerging Technologies (ICEET 2023)* ***(Published)***.

[6]. Arifa Haroon, Shabana Ali, **Ubaid Umar**, Sadia Farooq, Tayyaba Fahad, Tayyaba Qureshi. 2025. "Histopathological Effects Of 4G And 5G Electromagnetic Radiations on Liver Tissue" in *Journal of Rawalpindi Medical College* ***(Published)***

[7]. Arifa Haroon, Shabana Ali, **Ubaid Umar**, Sadia Farooq, Tayyaba Qureshi, Tayyaba Fahad. 2025. "Neuroanatomical Alterations in the Rat Auditory Cortex Induced by Fourth and Fifth Generation Wireless Radiation Exposure: A Laboratory-Based Experimental Study" in *Journal of Life and Science* ***(Published)***

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[9]. Salman Waheed, Aqdas Naveed Malik, Ihsan ul Haq, Muhammad Rizwan, **Ubaid Umar**. 2025. “Detecting Mode Collapse in GANs via Latent Space Sensitivity Analysis” in *11th International Conference on Engineering and Emerging Technologies (ICEET 2025)* ***(Published)***.

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[11]. Muhammad Fahad Munir, Abdul Basit, Athar Waseem, Mardeni Bin Roslee, Wasim Khan, and **Ubaid Umar**. "Cognitive Fusion of Radar and Communication Functions: Deep Learning Perspectives." in *Multimedia University Engineering Conference (MECON 2024)* ***(Published)***.

[12]. Ammar Armghan, **Ubaid Umar,** Muhammad Sinan Ateeq Khan, Ussama Assad and Fawad Naseer. 2012. “Modeling and Simulation of ADS6445 Using VHDL” in *International Conference on Electronics, Communications and Control* ***(Published)***.

This thesis covers research work based on publications mentioned from 1 to 3.

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Ubaid Umar

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List of Abbreviations

5G	Fifth-Generation
6G	Sixth-Generation
AI	Artificial Intelligence
AMP	Approximate Message Passing
AR	Augmented Reality
ASL	Accurate Structure Learning
AUD	Active User Detection
B5G	Beyond Fifth-Generation
BiGAMP	Bilinear Generalized Approximate Message Passing
BiMSGAMP	Bilinear Message Scheduling Generalized Approximate Message Passing
BS	Base Station
B-SBL	Block Sparse Bayesian Learning
CE	Channel Estimation
CIR	Channel Impulse Response
CS	Compressed Sensing
DD	Data Detection
DFT	Discrete Fourier Transform
Embb	Enhanced Mobile Broadband
HetNet	Heterogeneous Network
IoT	Internet of Things
JADD	Joint Activity and Data Detection
JCE	Joint Channel Estimation
ML	Machine Learning
MAMP	Memory Approximate Message Passing
mMIMO	Massive Multiple Input Multiple Output
mMTC	Massive Machine-Type Communication
MMV	Multiple Measurement Vector

MU-MIMO	Multi-User MIMO
NOMA	Non-Orthogonal Multiple Access
NMSE	Normalized Mean Squared Error
OFDM	Orthogonal Frequency Division Multiplexing
OMP	Orthogonal Matching Pursuit
OMP-IR	Orthogonal Matching Pursuit with Iterative Refinement
OMPe	Enhanced Orthogonal Matching Pursuit
OAMP	Orthogonal Approximate Message Passing
SIC	Successive Interference Cancellation
SNR	Signal-to-Noise Ratio
SSL	Simplified Structure Learning
THz	Terahertz
UE	User Equipment
UAPs	User Activity Patterns
VR	Virtual Reality

List of Symbols

α_k	User Equipment activity
B_s	Two-sided bandwidth
$\beta_{k,l}$	Complex path gain
$d_{p,k}$	Equivalent CIR vector
F	Discrete Fourier Transform matrix
$F\|_{\xi}$	Submatrix of F comprised of K_r rows and N columns
Ka	Number of Active Users
$h_{p,k}$	k-th user's subchannel
L	Number of Multipath Components
M	Number of Antennas
Mg	Number of Antenna Groups
N	Subcarriers
n_p^t	Additive white Gaussian noise
N_p	Pilot subcarriers and in n-th antenna group
Ng	Number of Antennas in One Group
P	Number of Pilots
R	Distance from Base Station
$s_{p,k}^t$	Uplink pilot
S	Sparsity Level
SF	Sub-Circle Factor
$S_{k,p,l,\psi_{k,l}}$	pilot data of k^{th} user
$y_{p,k}^t$	Received signal
ξ_n	The index set of pilot subcarriers
$\phi_{k,l}$	Angle of arrival
$\overline{\omega}_{k,l}$	Path delay
ψ_{z,r_s}	Sensing matrix
ϵ	Noise variance

CHAPTER 1

INTRODUCTION

This chapter provides a comprehensive overview of the research context, focusing on the challenges and opportunities in fifth-generation (5G) wireless communication systems. The emphasis lies on Massive Multiple-Input Multiple-Output (MIMO) systems, which form a foundation of 5G technologies. We also explore the critical aspects of channel estimation (CE) and active user detection (AUD), presenting the problem statement and research objectives. This research suggests a compressive sensing (CS)-based approach to cater these challenges.

1.1 Background and Motivation

The introduction of fourth-generation (4G) wireless communication systems marked a transformative milestone in global connectivity, enabling widespread access to faster and more reliable networks. However, as the number of wireless devices and services continues to soar, 4G networks face challenges such as limited spectrum availability and suboptimal energy efficiency. Evolution towards 5G and B5G systems is driven by the increasing request for higher data speeds, uninterrupted mobility, and support for developing applications. Deployment of 5G networks has been done in many regions across the world since 2021, which aims to achieve notable developments, including up to ten times faster data rates, 100 times better energy efficiency, 1000 times greater system capacity than its predecessor [1].

Recent developments in 5G wireless networks are revolutionary for future wireless networks and further speedy developments towards the B5G networks, to meet the increasing demands is a revolutionary way forward. 5G and B5G technologies are designed and expected to fulfil the requirements of ultra-reliable low-latency communication (uRLLC), enhanced mobile broadband (eMBB), and massive machine-type communication (mMTC). These wireless communication networks are comfortably meeting the demands and facilitating the evolution of the cutting-edge applications such as augmented reality (AR), virtual reality (VR), and the expansive Internet of Things (IoT) [2].

However, as we move forward towards their applications, we are facing different challenges in successful implementation of these technologies which needs immediate attention to fully incorporate these technologies. Two of the main challenges faced by these technologies, which are mainly the focus of this research as well are CE and AUD within Massive MIMO framework. The aspect of security is another feature, that is focused in this research, which is one of the biggest challenges for current wireless communication systems. Multiple users are simultaneously served by the Base Transceiver Station using the large antenna arrays. By incorporating this feature, the spectral and energy efficiency of the system has increased many folds due to parallel data transmission through multiple devices, using the same frequency band. We need to address a lot of challenges other than these to fully realise such systems and to achieve maximum output from these technologies, and emerging techniques are required to fulfil the purpose because traditional techniques limit their potential [3].

1.2 Engineering Requirements for 5G

The evolution to 5G presents high hopes which stretch the limits of current wireless communication technology. To realize 5G's capabilities and fulfil its requirements, various important engineering challenges must be resolved to guarantee that the new network infrastructure will meet the massive demands of future connection. These requirements go beyond continual improvements over former technologies, demonstrating an important change in how wireless systems are developed and operated.

1.2.1 Data Rates

One of the major challenges for 5G is the requirement of boosting data capacity by up to 1,000 times compared to the earlier generations. Which means attaining the peak data speeds of 10 Gbps (gigabits per second), that is important for allowing bandwidth-hungry applications for example, ultra-high-definition video streaming, AR, and VR. For everyday users, it's also important that the data speeds at the edge networks are fast enough, ideally at 100 Mbps or more. This gigantic increase in data rate is essential to not only meet the ever-growing demand for faster internet but also to incorporate the wide range of devices, applications, and services that will be running simultaneously on 5G networks [4].

1.2.2 Latency

Latency is an important parameter for 5G. One of the most noteworthy improvements that 5G has brought is to decrease in latency to almost 1 millisecond, a considerable decrease from the 15-millisecond latency that is commonly seen in 4G networks. This decrease is important for allowing real-time applications that require instant communication, such as autonomous driving, remote surgeries, and real-time industrial automation. For these applications, even the smallest delay in communication can have a major impression on performance. Therefore, guaranteeing low latency is vital for 5G networks to successfully support these advanced use cases [4].

1.2.3 Energy and Cost Efficiencies

As 5G networks are applied on large scale to meet huge data rate and latency demands, it is important that they also are intended to be energy-efficient and cost-effective. With the many folds increase in data rates expected, the energy consumption of the network and the cost per bit of communication must decrease by 100 times. Achieving this level of energy and cost efficiency, is important for ensuring the long-term sustainability of 5G and B5G networks, both in terms of working costs for service providers and their impact on the environment. Novelties in hardware, network architecture, and resource management will be crucial in meeting these requirements without compromising performance [5].

Although these engineering specifications demonstrate the enormous complexity of 5G network architecture, they also demonstrate the revolutionary possibilities of 5G for a wide range of businesses. As 5G networks are put into place, they will open the possibilities for innovations that go beyond conventional telecommunications, such as the Internet of Things (IoT), smart cities, and currently undeveloped new applications.

1.3 Heterogeneous Networks

A modest yet highly effective method to increase network capacity lies in the planned deployment of smaller cells to meet the demand for higher data rates, which continues to grow by every passing day. The method of heterogeneous network (HetNet) is reforming the way in which communication networks are designed. In this approach, the coverage area size is decreased to repeat the frequency use which ultimately increase the spectral efficiency which in turn increase the number of users being handled by that network without incorporating the major changes to the network. Rate of frequency reuse is directly proportional to the size of covered area of the cell, the smaller the cell the greater will be the frequency reuse that will result in meeting the increasing demand for data transfer [6].

There are some other effects of this change too that are also considered as benefit of HetNet. One of the benefits for smaller area is that the power required by the transmitter will be reduced which in turn will reduce the power losses in transmission, that are greater at higher powers. This will not only improve energy efficiency but will also reduce the operational costs. Additionally, the smaller cell strategy offers improved coverage in formerly difficult-to-serve regions, such as rural areas, dense metropolitan surroundings, or venues with increased user densities, such stadiums, and big malls. Large, conventional cells frequently provide poor reception to consumers in these conditions. A better overall user experience is ensured by small cells' ability to send stronger and more dependable signals [6].

One of the benefits of small cells is that using the same internet connectivity these can be integrated with already deployed infrastructure. Using this integration, the data and signals can be routed through the internet in form of small packets and hence it can be deployed in different type of locations with flexibility than the other type of networks which uses macro cells. Another benefit of this type of infrastructure is that it requires less space and hence can be deployed in urban and sub urban environments where due to dense population, deployment of infrastructure is either costly or sometimes impractical.

Small cells can be of different types and each type can have different type of uses and designed for different types of environments. For example, Femtocells are deployed in residential of smaller commercial setups for a limited number of users having limited coverage area for a localized environment e.g., home and a small office etc. Small cells address coverage challenges while significantly improving indoor data speeds. Meanwhile, picocells, which are designed to provide wider outdoor coverage, help bridge gaps left by macro cells. These networks of cells function exceptionally well in public environments with heavy traffic, such as train stations, airports, and commercial centres, where traditional network infrastructure frequently finds it difficult to control congestion. Picocells improve connection in areas that are challenging to service with traditional towers by blending in seamlessly with the network [6].

Integrating small cells into HetNets increases network efficiency in addition to coverage and capacity. 5G and B5G systems require ultra-fast speeds, low latency, and reliable connectivity and in future networks devices are adaptable and more compact. Hence a flexible solution is developed to incorporate different types of cells according to the specific requirements of a site, that includes femtocells, picocells, and other types. This approach is an innovative step towards a time when connectivity will be reliable and seamless [6].

HetNets use a variety of small cells, as shown in Figure 1-1, that integrates femto, pico, micro, and macro base stations for synchronized and effective operation.

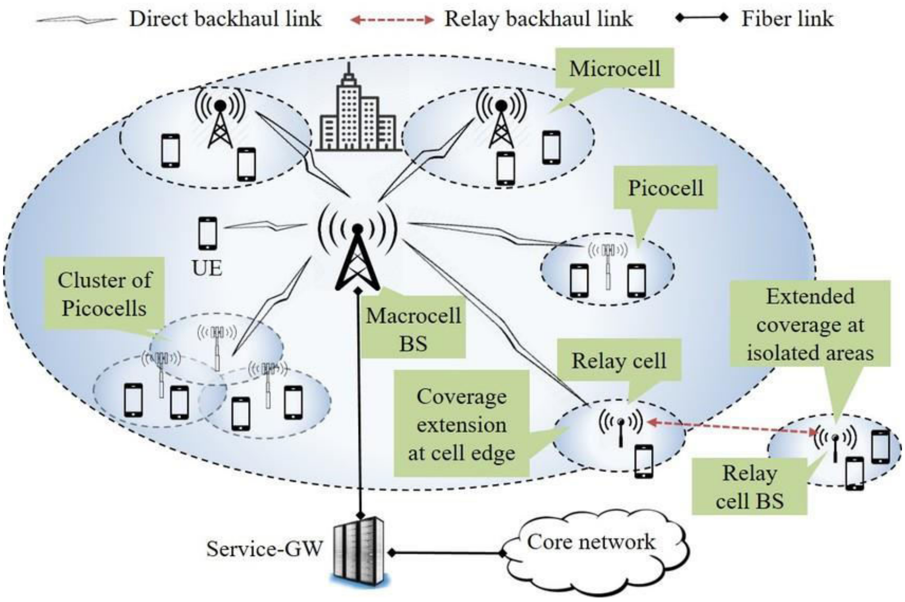

Figure 1-1: HetNets: integration of pico, micro, and macro base stations [7]

1.4 Millimetre Wave

Achieving higher data throughput is crucial for modern networks, and one effective strategy involves extending bandwidth. However, the limited availability of sub-6 GHz spectrum has pushed researchers to explore higher frequency bands. Among these, millimetre wave (mmWave) frequencies are emerging as a promising candidate for 5G systems.

Thorough evaluation of mmWave properties and benefits is essential before advancing its implementation. To pave the way for this technology, extensive measurement campaigns and channel modelling are required across diverse environments and scenarios. A lot of progress has already been made in mmWave communication infrastructure and it has been recognized an important infrastructure to achieve 5G and B5G performance goals. Spectrum of mmWave spans from 30 GHz to 300 GHz having wavelengths between 10 mm to 1 mm, is shown in Figure 1-2. An example of a network that incorporates mmWave technology along with macro cells is shown in Figure 1-3.

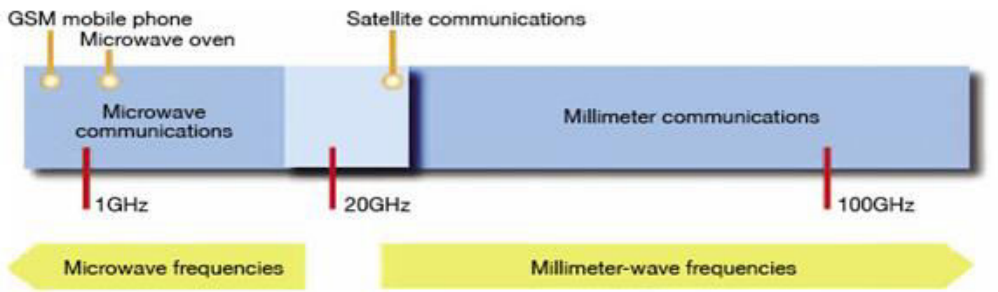

Figure 1-2: mmWave frequency range [8]

Studies have been done on mmWave frequencies, such as 28 GHz and 38 GHz, and different characteristics have been observed while communicating using these frequencies where mmWave has performed exceptionally well. Integrating mmWave in communication architecture has been researched thoroughly as outlined in [9] has produced good outcomes.

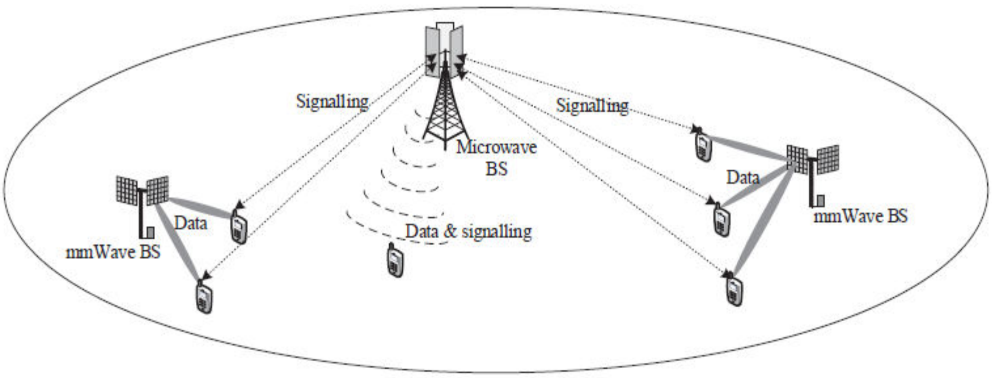

Figure 1-3: Millimetre wave enabled network with macro cell [10]

1.4.1 Key Advantages of Millimetre Waves

Untapped Spectrum: The mmWave spectrum remains mostly under-utilized, offering vast deployment opportunities.

Expanded Bandwidth: Broad range of bandwidth can be accessed, which is characteristic of modern communication systems.

Faster Data Rates: It offers higher speeds to fulfil the requirements of the modern communication applications.

Enhanced Security and Privacy: It provides secure communication environment ensuring higher level of protection and privacy [9].

1.5 Massive MIMO

Massive MIMO represents a considerable advancement in wireless communication, which has redefined the way the devices connect in the modern communication environments. Contrast to the conventional MIMO systems, that use a small number of antennas at both the transmitter and receiver end, the Massive MIMO takes this concept to the advanced level by incorporating large antenna arrays, often numbering from dozens to even hundreds, on both the transmitter and receiver ends of the communication system. Although it seems a simple change in the size of the hardware, yet its effect on the communication system is huge, which offers higher bandwidth capability, more reliability and enhanced overall efficiency of the system than the previous ones [11].

A salient feature of the Massive MIMO is that it can be expanded both in time and frequency domain and leverage the freedom in expansion. Hence more simultaneous data can be transferred which in result becomes the reason to incorporate a greater number of users simultaneously without facing any congestion in the network, that was very frequent in previously available techniques in dense user environments. Due to demand of higher number of users from cutting-edge technologies like IoT, the higher data demand has become very crucial. The Massive MIMO does not only deliver and fulfil such demands but also considered to be most reliable in term of quality of service [12].

Massive MIMO increases the throughput of the data and performs well in terms of energy efficiency. These antenna arrays perform tasks in multi cell scenario as shown in Figure 1-4 and beamforming scenario in single cell as shown in Figure 1-5. Carbon footprint of latest technologies is very critical aspect of evolving communication systems and Massive MIMO has served the purpose to reduce the carbon footprint and prove to be a greener technology than the previous ones. Also, the radio spectrum has been becoming a precious resource with the advent of wireless technologies and incorporation of increase number of devices in the network. Massive MIMO has also helped in reducing the bandwidth requirements by incorporating frequency reuse in dense or populated areas. All the above improvements make Massive MIMO a key player in the sustainable development of mobile networks [13].

Beamforming is a critical technology that aids to the Massive MIMO, which enables the wireless networks to precisely direct the energy towards specific targeted user instead of wastage by directing it to wider area. Beamforming is sending directional data instead of broadcasting and hence improves the energy efficiency of the system. By following these directional energy signals not only saves the energy but also provide good quality of service, which is also a main target or requirement of a communication system.

CSI is very important characteristic of a communication system where beamforming is being used as it provides a detail insight into the established link and shows behaviour of the link. Signals or data can be transmitted to the actual receiver if the established link is carefully selected and targeted, which in turn maximize both the speed and reliability. In dense user environments where the complex scenarios are deployed maintaining a seamless environment is very crucial [14].

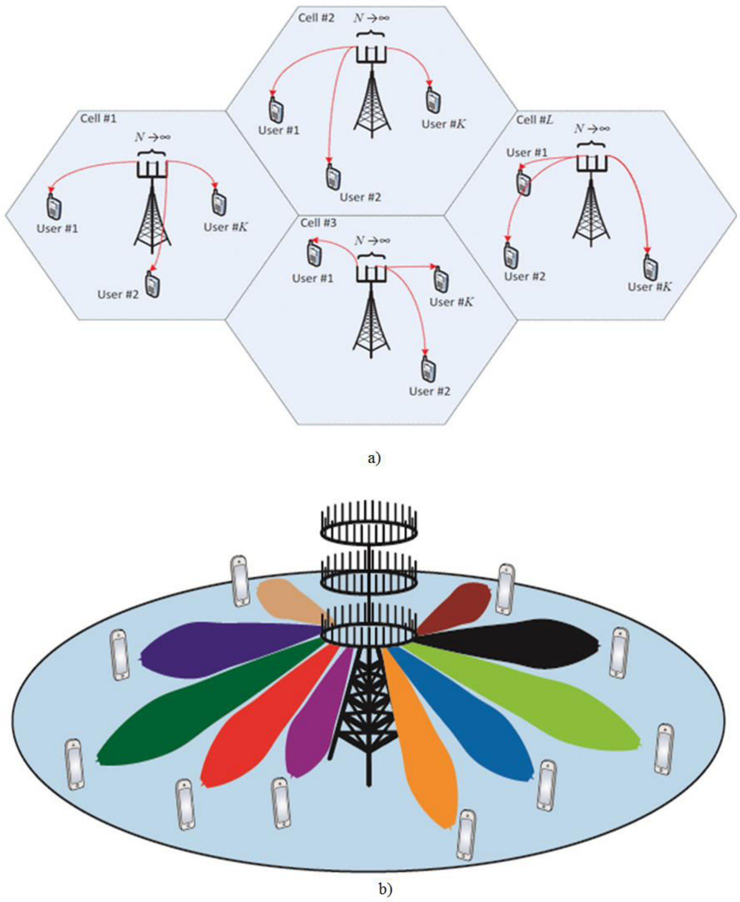

Figure 1-4: Massive MIMO: a) multi cell scenario b) beamforming in single cell [11]

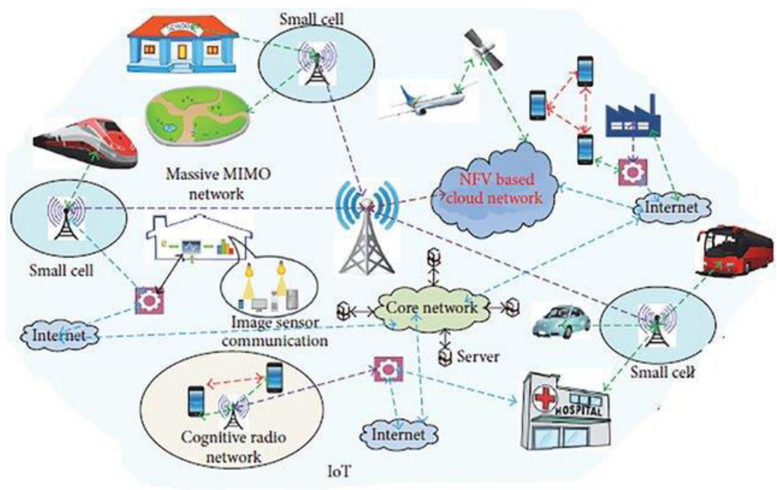

Figure 1-5: A 5G heterogeneous network along with large MIMO [13]

Another advantage of the Massive MIMO systems is that, many antennas can be arranged nearby areas or collocated on a single location, which provides deployment flexibility. Different operational requirements can be adapted leveraging this flexibility as in dense urban or sub-urban environments with large number of users. In such application areas antennas may be placed at a single location, means collocated in form of a compact array, ensuring the power efficiency and higher signal strength and in some other cases these antennas can be placed at wider or far sites to incorporate more diverse requirements to cover multiple zones. Due to this flexibility of the system, it is ensured that it can be deployed at multiple sites or geographic locations to incorporate specific challenge posed by an application of the communication system.

At the receiver end, antennas can be arranged in various ways, either grouped within a single site or distributed across multiple sites, depending on the requirements of the application. In urban areas, where signal interference and network congestion are common challenges, a distributed antenna system can improve connectivity by navigating obstacles like building towers and densely populated commercial areas. Centralized arrangement of antennas performs well in smaller areas like gyms and stores. Performance of such architectures proven to be best in smaller areas with changing user requirements [15].

Another advantage of Massive MIMO is that it addresses challenge of Fading, noise, and inter-cell interference. As user changes the location, fading occurs and the signal strength fluctuates. Different sources of noise e.g., electrical sources, environmental factors etc. worsen the quality of the signal. Overlapping between adjacent cells is called inter-cell interference which causes disturbance which is also a cause of signal degradation. Massive MIMO characteristically uses advanced detection methods and linear precoding techniques to effectively counter these challenges, which ensure stability and reliability.

Massive MIMO when enhanced as a Multi-User MIMO (MU-MIMO), serves multiple users at once without any additional interference and multiple users transmit data using same frequency band. This multi user connectivity is very much useful in dense environments [16].

By incorporating all the advanced technologies like large antenna arrays, beamforming, precise CSI, and multi-user functionality, designed systems turn to meet all the requirements of 5G and B5G networks. The possibilities unlocked by this technology mark a significant step forward in our ability to connect and communicate.

1.6 Challenges in 5G and Beyond 5G Systems

As we are entering into the era of 5G and B5G, engineering challenges grow increasingly complex. These networks are designed to support far a greater number of users, handle larger data volumes, and power sophisticated applications. Solution for these challenges is critical to realize full potential of 5G and to ensure that the future networks meet the rising demands of mobile and IoT connectivity.

1.6.1 Channel Estimation in Massive MIMO Systems

Accurate channel estimation is critical for ensuring reliable communication in Massive MIMO systems, it significantly influences efficiency of the spectrum, energy, and resistance to the interference. However, the unique characteristics of 5G and B5G systems introduce several challenges such as pilot contamination and high dimensional matrices.

Pilot Contamination

In Massive MIMO, reliable communication can be ensured with accurate estimation of channel characteristics. In multi user environment it is very difficult to ensure this accuracy. Pilot contamination causes a critical hurdle [17].

High-Dimensional Channel Matrices

Large number of antenna arrays are used in Massive MIMO that ultimately results in high dimensional data matrix, which is computational difficult to estimate. With an increasing number of antennas and users, real-time estimation becomes even more challenging. To solve this challenge efficiently, innovative signal processing algorithms and advanced mathematical tools are required [18].

Sparsity Exploitation

Interestingly, wireless channels in 5G often exhibit sparsity in the angular domain due to environments with limited scatterers. This property can be leveraged to reduce the computational demands of channel estimation. CS techniques, such as Orthogonal Matching Pursuit (OMP) and its enhanced versions like OMP-IR, capitalize on sparsity to deliver accurate estimates with less measurements. These methods not only tackle pilot contamination but also make high-dimensional matrices more manageable, enabling reliable operation in high-density networks [19].

1.6.2 Active User Detection (AUD)

A prominent feature of 5G and B5G networks is the promise of massive connectivity. Specifically, in massive Machine Type Communication (mMTC) scenarios, billions of devices, many of which will only be occasionally active, also need to communicate. For efficient network operation, AUD becomes critical. It allows the system to identify which users are active at a given time, enable the network to allocate resources efficiently and manage interference effectively. In AUD systems face certain challenges, which should be handled efficiently [20].

Sparse User Activity Patterns

In many IoT and mMTC applications, only a small subset of users are active at a time. It is a very difficult task to detect those in large number of devices. In large scale networks it becomes more difficult. Therefore, AUD techniques need to be scalable and capable of handling the total volume of data from large number of users' database, and ensure that only the active users are identified and served.

Noise and Interference

AUD in presence of noise and interreference add to the complexity of already complex systems. Signal-to-noise ratio (SNR) may vary significantly and frequently in real environments especially in difficult terrains. Already weak signals in such areas become more difficult to detect due to this background noise and interference. Efficient detection algorithms are required to be robust enough to handle these changing conditions and still correctly identify the active users.

Computational Complexity

Handling computational complexity is another challenge that different conventional techniques encounter. In applications where latency in critical and cannot be compromised, computationally inefficient techniques struggle to produce efficient outcomes. The computational burden of detecting active users in massive networks become unaffordable. This requires the development of more efficient algorithms that may detect active users without increasing the burden on the processing capabilities of the system [21].

Compressed Sensing based AUD

One important method to solve these challenges is the use of Compressed Sensing-based methods for AUD. By exploiting the sparsity of user activity pattern, these methods can efficiently detect active users with limited number of measurements than traditional larger measurements. Enhanced OMP along with other advanced techniques have shown significant improvements in accuracy of the detection, even under low SNR conditions. Moreover, the integration of chaotic sequence-based methods has further enhanced detection performance by increasing the robustness of the system, making it stronger against interference and noise [22].

1.6.3 Security in 5G and B5G Networks

As we move towards 5G and B5G systems, the large number of connected devices and the complexity of the network create several security challenges, which become more challenging in B5G where heterogeneity of large number of devices and increase risk of coordinated cyber-attacks are expected. It is very critical to ensure that data transmission is secure, specifically in an environment where every device, from smartphones to IoT sensors, is connected to a large network.

Eavesdropping and Data Integrity

One of the main security threats in 5G and B5G networks is the risk of eavesdropping and data manipulation. As the number of connected devices increases, so does the possibility for unauthorized access to sensitive and important data. The risk of interception, through several kind of attacks, becomes a high concern. To mitigate these risks, advanced encryption and authentication mechanisms are essential. Furthermore, the integrity of the data must be protected from malicious elements.

Complex Pilot Design

Pilot contamination is an important issue in channel estimation, especially in massive MIMO systems. Along with this, pilot-based methods for channel estimation come with their own set of security risks. One such risk is pilot spoofing attacks, where a malicious device sends false pilot signals, which can disturb the channel estimation process and harm the overall security of the system. To handle this problem, it is important to not only design more secure pilot sequences but also create procedures that can authenticate these pilot signals in real time.

Lightweight Security Solutions

Many of the devices that are connected to 5G and B5G networks especially under IoT framework, are highly resource hungry and due to smaller size, they may have limited capabilities hence security solution must not require heavy resources from such devices. This issue can be addressed with light weight security solution and work is being done to fulfil this demand. In this context, chaotic sequences have appeared to be a powerful tool. Inherent randomness and unpredictability make them ideal for securing data transmission with smaller overhead. Chaotic sequences have emerged as an innovative approach to enhance the security [23]. However, looking at the broader cyber threat landscape in B5G the need for more advanced security protocols arises, such as physical-layer key generation, homomorphic encryption, post-quantum cryptography, and blockchain-assisted authentication, are some of the techniques that ensure long-term resilience.

1.7 Problem Statement

The rapid expansion of wireless communication has brought about an ever-growing demand for systems that are not only efficient but also reliable and capable of scaling to meet future needs. As we move into the era of 5G and beyond, Massive MIMO systems have emerged as a foundational technology. These systems promise significant gains in spectral efficiency and energy usage, but their success hinges on overcoming critical challenges, such as obtaining accurate channel state information and effectively identifying active users in increasingly dense networks.

In Massive MIMO systems, channel estimation and active user detection are particularly complex tasks. The high dimensionality of data, combined with the sporadic nature of user activity and the dynamic characteristics of wireless environments, makes these processes demanding. Traditional methods for channel estimation, like Least Squares and Minimum Mean Square Error techniques, often fall short when faced with limited pilot resources or low signal-to-noise conditions. Similarly, conventional active user detection approaches struggle to handle the massive connectivity and unpredictable user behaviour that future networks demand.

Adding to these challenges is the need to exploit the unique features of Massive MIMO systems, such as spatial sparsity and angular domain properties. Although emerging techniques like compressed sensing and machine learning-based solutions show potential, they are often hindered by high computational demands and difficulties in adapting to real-world scenarios. On top of these technical challenges, ensuring secure and private communication in these systems remains a critical issue, particularly in the context of evolving threats and the need for data protection, which can be further addressed to achieve better results.

This research seeks to tackle these pressing challenges by developing advanced solutions for channel estimation and active user detection especially for Massive MIMO systems. The focus will be on designing algorithms that harness sparsity in spatial and angular domains, integrate advanced compressed sensing techniques, and explore novel methods to enhance security, such as the use of chaotic sequences. By bridging the gap between theoretical advances and practical deployment, this work aims to contribute to the development of robust, scalable, and secure communication systems that meet the demands of 5G and beyond.

1.8 Research Objectives

This thesis aims to address the challenges discussed above through achieving the following objectives:

- Development of enhanced Compressed Sensing-based channel estimation technique by exploiting spatial and angular sparsity in Massive MIMO systems.
- Proposal of novel Active User Detection scheme in high-density scenarios.
- Evaluation of the proposed solutions in simulated 5G/B5G environments to validate their performance in terms of accuracy.
- Exploration of security enhancements using chaotic sequences to protect channel estimation processes against adversarial attacks.

By addressing these objectives, this research contributes to the development of more efficient, secure, and scalable communication frameworks for 5G and B5G networks.

1.9 Main Contributions

1.9.1 Development of Enhanced OMP Algorithm

An enhanced OMP algorithm is derived using the traditional OMP framework by leveraging the limitations

Indexing Refinement

To prevent the selection of redundant indices a unique index refinement is introduced to ensure efficient and accurate support set updates during an iteration. In high dimensional data for dense user environment, it has improved the selection mechanism.

Orthogonalization Enhancement

Enhanced the orthogonalization process by incorporating dimension handling techniques, including zero-padding, to ensure compatibility with real-world datasets and improved reconstruction accuracy by refining the pseudo-inverse computation for sparse recovery.

Backtracking Mechanism

Designed a backtracking strategy to monitor the residual improvement and revert to previous steps if progress stagnates then added a fail-safe mechanism to optimize convergence, especially in scenarios with low SNR.

Iterative and Adaptive Refinement

Integrated iterative refinement within a limited set of iterations to strike a balance between computational complexity and reconstruction accuracy and included adaptive convergence checks, enabling early termination when residuals fall below a predefined threshold, thus optimizing processing time.

1.9.2 Performance Evaluation

Conducted a comparative analysis of OMP, OMP IR, and the proposed Enhanced OMP under various conditions of channel sparsity and user density and demonstrated superior performance of Enhanced OMP in terms of residual minimization, accuracy of active user detection, and computational efficiency.

1.10 Impact of Contributions

1. Enhanced Channel Estimation: Achieved higher accuracy in estimating sparse channel vectors due to the inclusion of advanced orthogonalization and indexing strategies.
2. Improved Active User Identification: Enabled precise detection of active users in scenarios with dense connectivity, leveraging adaptive and iterative refinement techniques.
3. Reduced overall computation time through early termination and efficient residual refinement mechanisms.

These advancements collectively address critical challenges in massive MIMO systems, providing a robust framework for real-world applications in 5G and beyond. My contributions establish a foundation for future enhancements in compressed sensing algorithms and their applications in communication systems.

1.11 Thesis Organization

Rest of the thesis is organized as follows:

Chapter 2 takes a deep dive into the existing literature, summarizing previous research and key findings relevant to this work. It explores how others have approached challenges in channel estimation, user detection, and system security in 5G and beyond technologies.

The review also covers developments in compressed sensing, machine learning, and chaotic sequences that have shaped wireless communication strategies.

Chapter 3 explains the methodology behind our research in detail. We introduce concepts like spatial and angular sparsity and how these phenomena influence our system model. The chapter outlines the design choices for antenna groupings, pilot sequences, and sub-circular designs in the one-ring channel model. We also discuss how compressed sensing techniques, especially with chaotic sequences like the logistic map, can enhance the accuracy and efficiency of channel estimation and active user detection. Finally, we describe the new compressed sensing algorithm developed as part of this study.

Chapter 4 presents the results of the experiments conducted during the research. The analysis focuses on various factors affecting channel estimation, such as antenna array size, user density, and subcarrier configurations. We discuss the impact of these elements on the mean squared error (MSE) and draw conclusions based on these findings. Additionally, we analyse the active user detection process, investigating how factors like the number of antennas, signal-to-noise ratio, and the number of active users affect the system's performance.

Chapter 5 is the final chapter, summarizes the key takeaways from the research, highlighting the contributions made, particularly the development of an OMPe algorithm. Practical implications of these findings are discussed and offer several recommendations for future research. These include exploring advanced sparse recovery techniques, optimizing the system for real-time applications, and enhancing robustness under more complex environments. Ways to integrate emerging technologies are also discussed, to improve security measures, and ensure the scalability of solutions for ultra-dense network environments.

CHAPTER 2

LITERATURE REVIEW

The gradual evolution into 5G and beyond networks brings the promise to entirely redefine both innovation and connection in the constantly altering field of wireless communication. MIMO communication systems, renowned for offering exceptional improvements in spectrum efficiency, system reliability, and energy efficiency, are leading this innovation. The deeper the intricate landscape of 5G and beyond is investigated, the more noticeable it becomes that critical challenges, primarily concerning channel estimation and active user detection, must be dealt with before massive MIMO technology can fulfil its potential. Systems based on Massive MIMO are complicated, face constraints in terms of pilot resources, and operate with large channel matrices. This causes navigating this complication effectively to be tough and requires us to come up with creative solutions [12][24].

Massive MIMO (Multiple Input Multiple Output) technology, upon which 5G networks and vital to upcoming 6G are built, makes use of large arrays of antennas to cater to multiple users over the same time-frequency resources. This technology raises the efficiency and capacity of networks by increasing spectral efficiency, bolstering signal quality, and lessening interference [25]. Active User Detection (AUD) is very critical in these systems that determines active users in many devices. Efficiency of the AUD improves with CS as it can process natural quality of activities of the users which translates into the user detection with minimal data [26][27]. Less number of measurements to detect active users with minimum computational load is very critical to improve the performance where number of users are increasing manifolds [28]. CS-based channel estimation system efficiently applies iterative recovery algorithms using adaptive measurement matrices. Structured sparsity in the angular area is used in this technique to improve estimation precision while reducing computational load. Certain sparse recovery techniques are focused to optimize the accuracy of channel estimation in massive MIMO technologies. The research they generate places emphasis on advanced sparse recovery algorithms for the solution of channel estimation in high-dimensional spaces, which yields more accurate and efficient outcomes. Considering the massive access environment in MIMO, AUD and channel estimation is performed exploiting the sporadic behaviour of devices. The proposed generalized multiple measurement vector approximate message passing (GMMV-AMP) scheme supports massive access by keeping low latency [29]. User activity detection along with estimation of fading coefficient is carried out using Maximum Likelihood algorithm. Number of active users as compared to number of antennas should be lesser but in massive access it is a bottleneck which can be overcome by increasing the number of antennas at base station [30].

Cell free MIMO systems is considered with large number of users maximization-approximate message passing (EM-AMP) algorithm is used for CE. Proposed scheme estimates channel coefficients by priori distribution and for small pilot length the proposed scheme has given exceptional results and more importantly very less prior information is required for processing [31]. Common sparsity in the received pilot patterns was not fully exploited along with the decoding information of the channel. Performance of the systems improves when user detection is jointly performed with data decoding and channel estimation [32]. To reduce the overhead requirements where large number of users are using MIMO grant free scheme is proposed in which pilots are uniquely assigned that are non-orthogonal. Bilinear generalized approximate message passing (BiGAMP) algorithm applied for sporadic traffic [33]. Bilinear message-scheduling GAMP (BiMSGAMP) algorithm is used for channel estimation along with data decoding. Messages are scheduled and evaluated in each iteration to achieve better results of estimation [34]. Asynchronous grant free access is explored as grant free massive access can be hard to realize and can less perform in practical scenarios. Here orthogonal approximate message passing (OAMP) is used to incorporate the common sparsity of the pilot signals and another algorithm is implemented to avoid the inverse in the system. Memory AMP (MAMP)-based algorithm reduces the complexity of the previous system [35]. By decreasing the length of the reference signal the performance of the Orthogonal Matching Pursuit (OMP) algorithm can be improved where after getting the path delay, the path gain is calculated and we see improved results in simultaneous OMP [36]. Security in Device-to-Device communication is the main concern while applying channel estimation. Resource deficient smart devices with limited power backup need efficient security schemes to give best performance with limited resources.

Cell-free communication has emerged as a promising approach to enhance grant-free transmission in massive machine-type communication. By enabling multiple access points to collaboratively serve numerous user equipment, it offers significant improvements in coverage and spectral efficiency. In [37] the authors introduce an innovative framework that integrates AUD, channel estimation (CE), and data detection (DD) for massive grant-free transmissions in cell-free systems. The optimization problem for joint AUD, CE, and DD was formulated by leveraging the sparsity of both the data matrix, resulting from sporadic user activity and the effective channel matrix, influenced by user activity and large-scale fading. To address this problem, a box-constrained forward-backward splitting algorithm is employed, delivering substantial enhancements in AUD, CE, and DD performance. The proposed framework's efficacy is validated through comprehensive simulation experiments, showcasing its potential for improving cell-free communication systems. In [38] the authors focused on detecting active devices and estimating their channels in the uplink of massive machine-type communication (mMTC) networks, incorporating channel correlation across antennas in massive MIMO (mMIMO) systems—a factor often overlooked in prior research. Three Bayesian learning algorithms were proposed, exploiting spatial correlation to achieve better performance in terms of normalized mean squared error (NMSE), activity error rate, and spectral efficiency (SE) compared to existing methods. The correlated AMP algorithm delivers the best results but requires prior knowledge of large-scale fading and device activity probabilities. To address this, the block sparse Bayesian learning (B-SBL) algorithm removes these dependencies but at a higher computational cost. The combined AMP-BSBL algorithm reduces complexity while maintaining B-SBL's advantages, offering a practical balance. These findings provide new strategies for improving channel estimation and device detection in mMTC systems. A framework was proposed for designing non-orthogonal signature sequences deterministically, using unimodular sequences with low correlation applied as masks to the discrete Fourier transform (DFT) matrix columns in [39] by leveraging algebraic techniques, the resulting signature sequence matrix achieves theoretically bounded low coherence. Another research presented in [40] explored the challenges of massive machine-type communications (mMTC) in providing low-latency, large-scale access for IoT devices. To overcome these challenges, a beacon-assisted, slotted grant-free access scheme was proposed alongside joint activity and data detection (JADD) algorithms. The problem was framed as a multiple measurement vector (MMV) compressive sensing task, utilizing the structural sparsity of uplink signals. Two detection algorithms, OAMP-MMV with simplified structure learning (SSL) and accurate structure learning (ASL), were introduced, along with channel coding and successive interference cancellation (SIC) techniques to improve detection performance. Simulation results confirm that these methods significantly outperform baseline approaches. In an effort to support massive-scale connectivity with low latency in machine-type communications, authors proposed an enhanced grant-free access scheme for AUD in [41]. Recognizing the sporadic nature of user communication, the algorithm detects active users based on activity patterns, with activity probabilities (UAPs) derived from past communication data. These UAPs were integrated into a CS framework for joint AUD and channel estimation. The approach used an expectation-maximization algorithm to efficiently estimate the UAPs, with an online method that dynamically updates these estimates. Numerical results highlighted the efficiency of UAP approximation in enhancing AUD performance. Consistent detection of active devices and channel estimation in a MIMO-OFDM-based grant-free non-orthogonal multiple access (NOMA) system, essential for supporting large-scale machine-type communication (mMTC) was focued in [42] by leveraging the correlation in channel frequency responses across OFDM subcarriers, a block-wise linear channel model was proposed, reducing the complexity of channel estimation. The joint active device detection and channel estimation problem was framed as a Bayesian inference task, and a turbo message passing algorithm is employed to solve it. Simulation results showed that this approach outperforms conventional algorithms in terms of accuracy and efficiency.

2.1 Emerging Trends and Opportunities

As we move forward from 5G to B5G communication systems, the emerging trends are becoming more evident due to the requirements of the latest techniques. These trends ensure to enhance the capabilities of the systems hence open new research and innovation avenues across various sectors for better outcomes [13].

2.1.1 Ultra-Dense Networks

These networks use innovative approach to cater many users for efficient spectrum management and utilization of other resources. They ensure stable network performance in congested environment, keeping the latency to minimum and maximum throughput. Ultra-Dense Networks offer better interference cancellation and combination with Massive MIMO produce better outcome in dense environments.

2.1.2 Energy Efficiency

With the advent of new and smart devices, energy consumption has become an important factor of network designs. Low powered WAN has proven to be a game changer in this area, which reduces the power requirements of the devices for wireless communication systems. More such innovations in this area can produce good results for smart devices, designed for remote locations.

2.1.3 Security

As the number of devices are increasing with every passing day, and the consumers are going through rapid transformation, the concern of security of these devices is increasing. Different encryption schemes are being designed to protect the consumer from misuse. Different schemes like chaotic sequences-based encryption techniques are being designed and traditional schemes are set to be replaced by them.

2.1.4 Artificial Intelligence and Machine Learning Integration

Artificial Intelligence (AI) and Machine Learning (ML) techniques is taking a bigger part in shaping the future of communication systems. These techniques can not only optimize and predict traffic patterns but can also automate network management tasks. The integration of AI and ML in design of these networks also presents an opportunity to create self-organizing networks.

2.1.5 Terahertz (THz) Communication

Growing demand of data for increased number of devices need higher data rates and faster speeds. Fulfilling these demands with already available spectrum is not possible hence Terahertz (THz) band has emerged as a solution to this problem and the band details are given in Figure 2-1. THz communication can easily address the demands of applications such as immersive virtual reality (VR), augmented reality (AR), and holographic communications. Biggest challenge of THz communication is attenuation which may be resolved with innovative techniques [43].

2.1.6 Blockchain for Network Management and Security

Blockchain technology can securely and transparently record transactions. It is currently being explored for applications beyond cryptocurrencies. In the context of B5G networks, blockchain can play an important role in enhancing security of the sensitive networks [44].

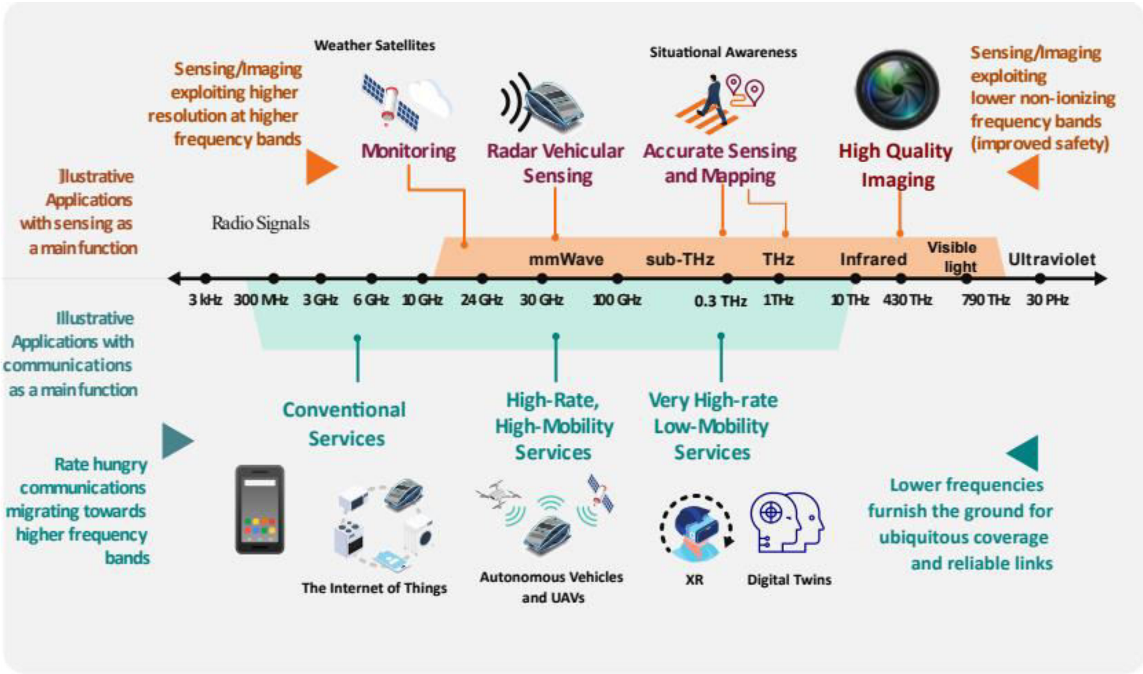

Figure 2-1 Terahertz Communication Band [45]

2.1.7 Smart Surfaces and Reconfigurable Intelligent Surfaces (RIS)

Reconfigurable Intelligent Surfaces (RIS) are made up of many low-cost, passive elements that can be programmed to reflect or refract electromagnetic waves in desired directions. Some of the use cases are given in Figure 2-2. RIS enhance signal quality and improve network coverage area. Integration of RIS in 5G and B5G networks holds enormous potential for enhancing network performance [46].

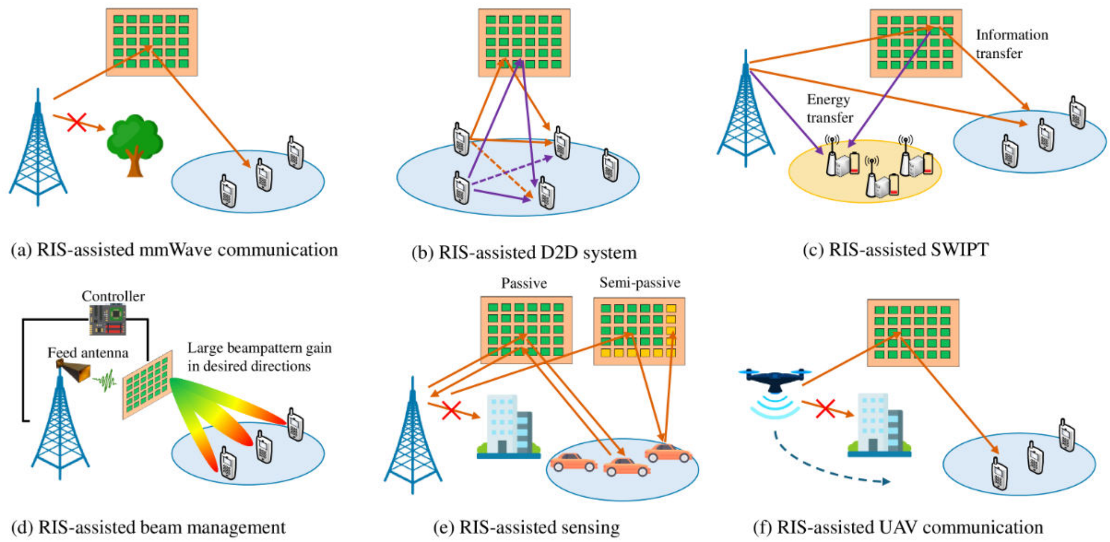

Figure 2-2 Six different use cases of Reconfigurable Intelligent Surfaces [47]

2.1.8 Edge Computing and Network Slicing

Edge computing is latest trend that is expected to contribute to the 5G and B5G networks. In these systems major data is processed at user end due to availability of the good processing devices hence the issue of latency is addressed in these systems.

Network slicing allows operators to create multiple virtual networks on top of a single physical infrastructure which also aligns with edge computing and can be user collaboratively.

These innovations offer exciting opportunities to meet the diverse and demanding needs of 5G and B5G applications, all while maintaining the flexibility and efficiency that is required for large-scale deployments [48].

This research particularly addresses the challenges of enhanced mobile broadband (eMBB) scenarios within massive access contexts in uplink massive MIMO orthogonal frequency division multiplexing (OFDM) systems. The sporadicity and inherent sparsity of user traffic in the angular domain (of massive MIMO channels) is exploited by applying Channel Estimation (CE) strategies. A new scheme is presented for flexible CE based on Compressed Sensing (CS), suited to the massive access, and based on an enhanced version of OMP. Furthermore, CS problem of CE is developed at the Base Station (BS) by leveraging the structured angular sparsity of the uplink channel matrix across space and angles. This outcome leads to the development of a Sparse CS based algorithm (OMP Enhanced) that caters to both spatial and angular domain channel models, enabling effective CE. The adaptive access strategy of the uplink channel matrix relies on its sparsity level to dynamically tune the access latency, or the extent of the access pilot sequence. This approach uses the structured sparsity among various subcarriers to raise CE performance.

To optimize the resource allocation and to minimize the interference, AUD plays an important role as established by the existing literature because of the inherent sparse nature of the dense user environments of 5G and B5G. Main idea to exploit this natural feature of sparsity digital signal processing-based techniques are very crucial especially CS. These CS based methods make maximum out of this sparse nature which in result provides more accurate user detection.

These enhanced algorithms are proving to be essential for addressing the increasing demands of next-generation wireless networks, such as 5G and B5G, where scalability, low latency, and high reliability are crucial. The capability to effectively detect active users in a dynamic and dense environment, along with minimizing the resource consumption and interference, is a foundation of the high performance required for such systems. As the number of connected devices and users continues to grow, these advances in AUD techniques will be helpful in maintaining the performance and reliability of future wireless communication systems.

CHAPTER 3

METHODOLOGY

3.1 Spatial Sparsity

Angular directions of multipaths between the receiver and transmitter are the reason of spatial sparsity. By knowing those angular directions one can use them in channel estimation to find the properties of the waveforms for example amplitude and phase of the waves. Spatial sparsity is determined by using its special correlation matrix in which eigenvalues will represent amplitude of a waveform in a specific direction and if there are some zeros in the eigen values means that amplitude or the waveform have no amplitude in a specific direction then this will be called spatial sparsity. For this sparsity to be utilized the number of antennas in the array must be very large to distinguish between multiple directions having waveforms and the directions having no waveforms. If the beam width is greater than the directional distance in channel paths its effect would smear out and we will have zeros instead of real values. Taking $\tilde{f}$ an equivalent Channel Impulse Response (CIR) in a massive MIMO scenario, the impact of spatial sparsity is given by [29][36]

3.2 Angular Sparsity

Users are located at very long distance from Base Station and it's not only the distance, there is a huge difference in elevation as well and due to difference in elevation there is also a change in number of scattering elements. Number of such elements are greater near the users which is located at low elevation whereas its number is very much less near the BS. Considering the ring channel model as shown in Figure 3-1 for a user that is located at long distance from the base station (i.e., D) having a lot of scattering elements around results in very small angular spread as r<<D termed as sparsity in angular domain [49]. i.e., "$\Delta \approx \arctan(r/D)$". Also for angular domain and for an individual channel for the k-th user and for the pilot subcarrier p, we can say:

$$\mathbf{d}_{p,k} = \mathbf{A}_R^H \tilde{\mathbf{h}}_{p,k}, \tag{3-1}$$

Where sparsity can be observed as $\left|\text{supp}\ \{\mathbf{d}_{p,k}\}\right|_c \ll M$. In all the wireless channels spatial propagation characteristics are the same hence the same scatterers will be affecting all the sub channels [30]. This results in a sparsity pattern which is common in frequency domain.

i.e.,

$$\text{supp}\{\mathbf{d}_{1,k}\}=\text{supp}\{\mathbf{d}_{2,k}\}=\ldots=\text{supp}\{\mathbf{d}_{P,k}\} \tag{3-2}$$

Hence in Massive MIMO it is referred as structured angular-frequency sparsity. These also show that there exists clustered sparsity due to less angular spread of multi path components having different angle of arrivals (AoA). These properties of angular domain sparsity will be exploited for Channel estimation.

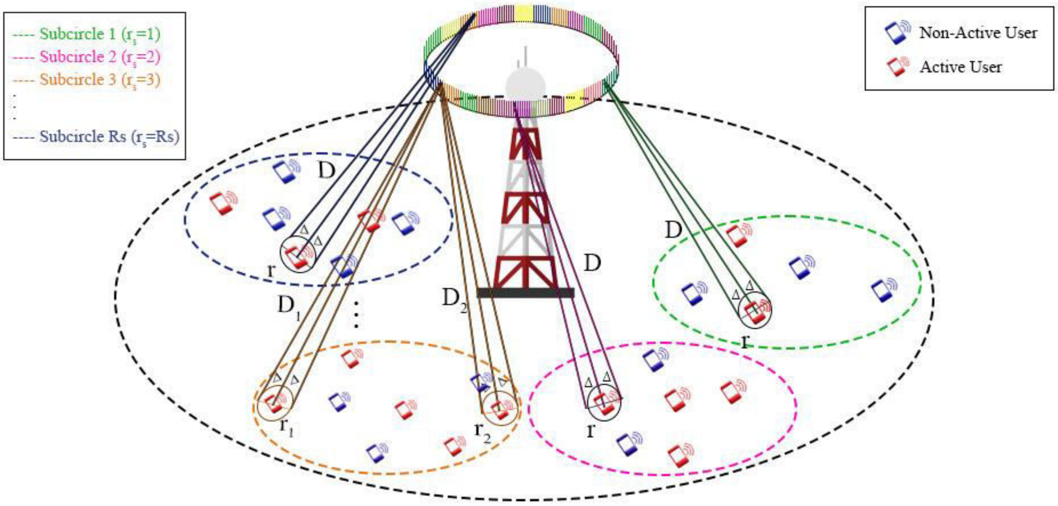

Figure 3-1: Sub-Ring Channel Model of active and non-active users in Massive MIMO (with sporadic behaviour)

3.3 Proposed Massive MIMO System Model

For massive MIMO systems we take a common scenario for uplink massive access. K potential users and an M-antenna array are present in a single base station. To counter time-dispersive channels, OFDM with N subcarriers is used, and the distribution of the Pilots P are even across subcarriers N. The t-th OFDM symbol or the signal $\mathbf{y}^{t}_{p,k} \in \mathrm{C}^{\mathrm{Mx1}}$received at the BS from the k-th user in time slot t for the subchannel of the p-th pilot subcarrier ($1 \le p \le P$) can be written as:

$$\mathbf{y}^{t}_{p.k} = \mathbf{h}_{p,k}\mathbf{s}^{t}_{p,k} + \mathbf{n}^{t}_{p}, \tag{3-3}$$

where the k-th user's subchannel is represented by $\mathbf{h}_{p,k} \in \mathrm{C}^{\mathrm{Mx1}}$, the k-th user's uplink pilot is represented by $\mathbf{s}^{t}_{p,k}$ and $\mathbf{n}^{t}_{p}$ is the additive white Gaussian noise that is received at the BS for the t-th time slot.

Here, we investigate single-antenna users without losing generality. In a typical massive access scenario, very few users are enabled and attempt to access the BS in the given amount of time. The indication of UE activity, represented by α_k, is 1 in cases where the k-th user is active and 0 in other cases. In the meantime, $K_a = |A|_c$ indicates the number of active users, and number of active users can be defined as the following set as $A = \{k|\alpha_k = 1, 1 \le k \le K\}$. As a result, at t-th time slot the signal for the p-th pilot subcarrier and the signal received by the BS from all active users is as follows.

$$\mathbf{y_p^t} = \sum_{k=1}^{K} \alpha_k \mathbf{h_{p,k}} \mathbf{s_{p,k}^t} + \mathbf{n_p^t} = \mathbf{H_p} \mathbf{s_p^t} + \mathbf{n_p^t}, \tag{3-4}$$

where $\mathbf{s}_{p,k}^t = [\mathbf{s}_{p,1}^t, \mathbf{s}_{p,2}^t, \ldots, \mathbf{s}_{p,K}^t]^T \in C^{Kx1}$ and $\mathbf{H}_p = [\alpha_1 \mathbf{h}_{p,1}, \alpha_2 \mathbf{h}_{p,2}, \ldots, \alpha_K \mathbf{h}_{p,K}] \in C^{MxK}$. We can express $\mathbf{h}_{p,k}$ as $\rho_k \tilde{\mathbf{h}}_{p,k}$ by taking both the small-scale and large-scale fading into account, where ρ_k represents the fading coefficient of large-scale, carried on by shadowing and path loss whereas $\tilde{\mathbf{h}}_{p,k}$ is the fading vector of small-scale. The subchannel of the p-th pilot subcarrier for k-th user is modelled as follows

$$\tilde{\mathbf{h}}_{p,k} = \sum_{l=1}^{L} \beta_{k,l} \mathbf{a}_R\left(\phi_{k,l}\right) e^{-j2\pi\varpi_{k,l}\left(-\frac{B_s}{2} + \frac{B_s\left(\frac{pN}{P}-1\right)}{N}\right)}, \tag{3-5}$$

where L is the number of all the multi-path components, B_s is the two-sided bandwidth $\varpi_{k,l}$ is path delay of the l-th multi-path component and $\beta_{k,l}$ is the complex path gain and also $\phi_{k,l} = \frac{d}{\lambda} \operatorname{Sin}(\varphi_{k,l})$. In this case, $d = \lambda/2$ is the antenna spacing, λ is the wavelength, and $\phi_{k,l}$ is angle of arrival of the k-th user's l-th multi-path component. For path delay $\varpi_{k,l}$ the AOA is $\varphi_{1,1} \simeq \varphi_{1,2} \simeq \cdots \simeq \varphi_{1,L}$ Similarly for all the other antennas the AoA will be the same for all the users in the circle, i.e., $\varphi_{K,1} \simeq \varphi_{K,2} \simeq \cdots \simeq \varphi_{K,L}$.

Because transmission distance is high whereas user exhibit similar kind of scatterers for a single antenna. Also because of the similar scatterers between long distant user and antenna, it exhibits similar path gains that will have similar pattern for active users (Ka) with respect to transmission for one antenna.

$$\mathbf{h}_{p,k,1} \approx \mathbf{h}_{p,k,2} \approx \ldots \approx \mathbf{h}_{p,k,Mg}, \tag{3-6}$$

There are always a small number of active users in the sporadic type of user's traffic. We have created antenna groups in circular regions, where all the users within that circular region exhibit spatial sparsity [36]. Thus $\mathbf{H}_p^{N_g} \in C^{K\times 1}$ observed for the p-th pilot subcarrier at the m-th receive antenna is sparse as supp $\left|\mathbf{H}_p^{N_g}\right|_c = K_a \ll K$. Also, all the antennas show same spatial sparsity.

$$\operatorname{supp}\left\{\left|H_{p,1,m_g}^{N_g}\right|_c\right\} = \operatorname{supp}\left\{\left|H_{p,2,m_g}^{N_g}\right|_c\right\} = \ldots = \operatorname{supp}\left\{\left|H_{p,M,m_g}^{N_g}\right|_c\right\}, \tag{3-7}$$

Additionally, users are placed in an environment with rich local scattering at low elevation far from the base station, but the base station is normally with few nearby scatterers at high elevation. The traditional one-ring channel model can be used to represent this scenario. The angular spread $\Delta = \arctan(r/R)$ observed from the Base Station is expected to be very minimal for a User situated at a distance R from the Station and surrounded by rich scatterers within a radius of r surrounding the User, as typically r << R. As a result, massive MIMO channels become sparse in the angular domain.

$$a_R(\phi_{k,l}) = \left[1\ e^{-j2\pi \mathrm{Sin}\varphi_{1,1}}\ e^{-j2\pi(\mathrm{Sin}\varphi_{1,1})2} \dots e^{-j2\pi(\mathrm{Sin}\varphi_{1,1})(M-1)}\right]^T, \tag{3-8}$$

Here, geometry of the assumed array describes $\mathbf{a}_R$, and becomes the DFT matrix for an array with $d = \lambda/2$. Because of the large M and small Δ, the channel vector $\mathbf{a}_R(\phi_{k,l})$is sparse i.e., $\mathrm{supp}\left\{\left|\mathbf{a}_R\left(\phi_{k,l}\right)\right|_c\right\} \ll M$ and this is strictly a clustered sparsity. Moreover, since propagation characteristics within the total bandwidth, for all wireless channels are similar for a user, same scatterers affect the subchannels across different subcarriers. To be more precise, for single user, all the channel paths will exhibit similar pattern as the transmission distance is high and the antenna spacing is much lesser. Consequently, the $\mathbf{a}_R(\phi_{k,l})\forall k$ have a common pattern of sparsity in the frequency domain as in Eq. (3-9) and for l-th path for one user in Eq. (3-10)

$$\mathrm{supp}\left\{\left|a_R\left(\phi_{k,1}\right)\right|_c\right\} = \mathrm{supp}\left\{\left|a_R\left(\phi_{k,2}\right)\right|_c\right\} = \dots = \mathrm{supp}\left\{\left|a_R\left(\phi_{K,L}\right)\right|_c\right\}, \tag{3-9}$$

$$\mathrm{supp}\left\{\left[a_R\left(\phi_{1,l}\right)\right]_{:,1}\right\} = \mathrm{supp}\left\{\left[a_R\left(\phi_{2,l}\right)\right]_{:,2}\right\} = \dots = \mathrm{supp}\left\{\left[a_R\left(\phi_{K,l}\right)\right]_{:,M}\right\}, \tag{3-10}$$

We have created antenna groups in a circular region where all the users exhibit spatial sparsity within the circular region. Total number of antennas at Base Station are M whereas there are N_g antenna groups each

having M_g number of antennas, according to formula provided in [16]. Where $\mathbf{h}_{p,k,1} = \mathbf{h}_{p,k,2} = \cdots = \mathbf{h}_{p,k,Mg}$. For every user in N_gth antenna group the equivalent CIR has similar sparsity pattern for each antenna in that group.

$$\mathrm{supp}\left\{h_{P,1,m_g}\right\} = \mathrm{supp}\left\{h_{P,2,m_g}\right\} = \dots = \mathrm{supp}\left\{h_{P,K,m_g}\right\}, \tag{3-11}$$

For circular geometry, where there exist N_g antenna groups, we can say that:

$$\mathrm{supp}\left\{\left|H_P^1\right|_c\right\} = \mathrm{supp}\left\{\left|H_P^2\right|_c\right\} = \dots = \mathrm{supp}\left\{\left|H_P^{N_g}\right|_c\right\}, \tag{3-12}$$

Based on outcome of the spatial and temporal sparsity provided in [36] and [40] and angular sparsity property in massive MIMO expressed above, the formulas for creating the antenna groups and pilot design are taken from [36]. Whereas the formula for creating sub-circular regions within a large-scale and highly dense communication regions is given by.

$$\Delta\theta \approx \arctan\left(\frac{r_1}{D_1}\right) - \arctan\left(\frac{r_2}{D_2}\right) = SF, \tag{3-13}$$

Where r_1 is the nearest user with least AoA and r_2 is the farthest user with maximum AoA, SF is the Sub-Circle Factor which can be controlled to design sub-circles by limiting the value of $\Delta\theta$.

3.3.1 Antenna Groups

Massive MIMO technology makes it feasible to transmit several data streams concurrently, which significantly improves spectral efficiency. Antenna arrays are made up of M antennas arranged in a particular way, such as circular. Beamforming, which concentrates the signal in a certain direction to improve signal strength and reduce interference, is made possible by these arrays. Ng Antenna groups are made up of smaller sets, or sub-arrays, of antennas. It is possible to independently control each group to serve a specific user or group of users, form beams, or direct signals.

3.3.2 Pilot Design

In modern wireless communication systems, especially in the context of 5G and beyond, the base station's ability to perform critical tasks such as beamforming, power control, and advanced signal processing heavily relies on obtaining accurate. It provides detailed insight into the characteristics of the communication channel, including path loss, fading, and interference, enabling the base station to make informed decisions regarding resource allocation, transmission power, and beamforming strategies. Without precise CSI, the efficiency of the communication network could be compromised, leading to suboptimal performance, increased interference, and reduced user experience.

To estimate the CSI, pilot signals are utilized. These pilot signals are known transmissions that are sent either from the base station or the users, which the receiver uses to estimate the channel's state. Pilots are essential because they allow the receiver to gather enough information about the channel conditions, which can then be used to decode the received signals more effectively. In essence, pilot signals act as reference points that help the receiver map the actual signal transmission against known values.

However, in multi-cell environments, the situation becomes more complex due to the limited availability of resources like time and frequency. Since the number of users is often very large and the available frequency spectrum is constrained, pilot sequences are frequently reused across different cells. This reuse leads to a phenomenon known as pilot contamination, which can severely degrade the accuracy of CSI estimation. When different cells transmit the same pilot sequences simultaneously or in overlapping time slots, it results in interference between the cells, making it difficult for the receiver to correctly estimate the channel and, consequently, reduce the efficiency of the overall system.

To address this issue, the proposed pilot design introduces a solution to mitigate pilot contamination. In this design, each sub-circle in the system operates with a fixed frequency, ensuring that users in the given sub-circle share the same frequency resource. However, the key difference lies in the allocation of different carriers to each user within the sub-circle. This ensures that while the frequency resource is reused across the cells, the carrier used for each user is unique, reducing the chances of interference between users in different cells, even if they are operating within the same sub-circle. This approach provides a more efficient way of utilizing the available spectrum while minimizing the risks associated with pilot contamination.

Furthermore, the proposed design extends this concept to all the antenna groups, as illustrated in Figure 3-2. Each antenna group follows the same principle, ensuring that the system scales efficiently while maintaining the integrity of CSI estimation. In this design different sub-circles represent user clusters separated based on spatial and angular parameters. Each sub-circle corresponds to a set of users served by a nearest group of antennas. Vertically, the figure is divided into antenna groups, indicating how the large antenna array is partitioned for more efficient pilot management and localized channel estimation. The third dimension, represented by stacked layers, shows pilot allocation across different frequency subcarriers. Within each sub-circle, only a subset of antenna groups and frequency resources are active for pilot transmission, that is shown by coloured blocks. Each colour represents a unique pilot sequence assigned to a user. Particularly, pilots are reused across different sub-circles in a structured manner, but to avoid interference it is ensured that pilot sequences are not reused in adjacent or overlapping regions. The black-and-white crosshatched areas may serve as guard zones or overlapping regions managed to avoid interference. This careful allocation ensures that pilot contamination is minimized as it poses a great challenge to Massive MIMO communication, while pilot resources are efficiently reused in spatially separated areas.

By adopting such a structured pilot sequence and carrier allocation approach, the system can achieve higher accuracy in CSI estimation, reduce interference, and ultimately improve the overall performance of the wireless network. This design not only contributes to better channel estimation but also sets the stage for more robust and efficient resource management in future wireless systems, where the demand for high capacity, low latency, and reliable communication will continue to increase.

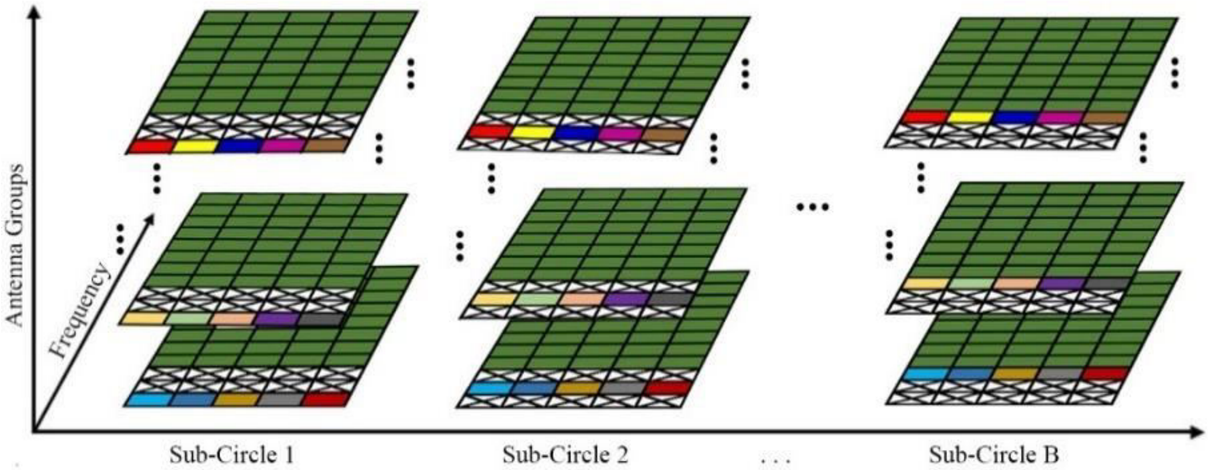

Figure 3-2: Proposed Pilot Design

3.3.3 Sub-Circular design in One Ring Channel Model

One ring channel model from [49] is further divided into sub-circles based on their distance from the antenna and angle of the user with the Base Station Antenna based on $\Delta \approx \arctan(d/D)$. Where Δ is limited to a specific value to divide the one ring into multiple sub rings based on Angular Sparsity.

Consider M transmit antennas in a massive MIMO OFDM system placed at Base Station that is interacting with one user, for nth antenna group ξ_n represents the index set of pilot subcarriers, the choice of ξ_n is taken from [36]. In one OFDM symbols there are total N subcarriers out of which N_p are pilot subcarriers and in n-th antenna group the pilot sequence of m-th transmit antenna is denoted by $\mathbf{s}_{m,n} \in C^{N_p x1}$**.** Where $\mathbf{y}_{z,n} \in C^{N_p x1}$ is the received vector of the pilot sequence of z-th OFDM Symbol of n-th antenna group at user for N_g antenna groups, $\mathbf{y}_{z,n}$ can be expressed as.

$$y_{z,r_s} = \sum_{k=1}^{K_r} \mathrm{diag}\left\{S_{k,p,l,\psi_{k,l}}\right\} F|_\xi \begin{bmatrix} d_{p,k} \\ 0_{(N-M_g)\times 1} \end{bmatrix} + w_k \tag{3-14}$$

Where $\mathbf{S}_{k,p,l,\psi_{k,l}} \in C^{K_r x K_r}$ is the pilot data of k^{th} user, $\mathbf{F} \in C^{NxN}$ is the Discrete Fourier Transform matrix (DFT) $\mathbf{F}|_\xi \in C^{K_r Xn}$ is a submatrix of $\mathbf{F}$ comprised of K_r rows and N columns, $\mathbf{d}_{p,k} \in C^{Nx1}$ is the equivalent CIR vector of m^{th} transmit antenna of n^{th} antenna group (There are N_g antenna groups each having M_g number of antennas) for z^{th} OFDM symbol, and $\mathbf{w}_k$ represents the Additive White Gaussian Noise for zth OFDM symbol of nth antenna group.

$$y_{\mathbf{z},r_s}=\sum_{k=1}^{K_r} S_{k,p,l,\psi_{k,l}} F_{M_g}\Big|_{\xi_{pd}} d_{p,k}+w_{z,n}=\sum_{m=1}^{K_r} \psi_{k,p,l,\psi_{k,l}} d_{p,k}+w_{z,n} \tag{3-15}$$

$\mathbf{F}_{M_g}\Big|_{\xi_{pd}} \in C^{K_r x M_g}$ is a submatrix of $\mathbf{F}$ comprised of K_r rows and M_g columns, selected according to [36], Where $\mathbf{S}_{k,p,l,\psi_{k,l}} \mathbf{F}_{M_g}\Big|_{\xi_{pd}}$ is replaced by $\boldsymbol{\psi}_{k,p,l,\psi_{k,l}} \in C^{K_r x M_g}$, $\mathbf{y}_{z,n}$ is expressed after exclusion of guard interval. The equation can further be rearranged as

$$\mathbf{y}_{\mathbf{z},\mathbf{r_s}} = \boldsymbol{\psi}_{\mathbf{z},\,\mathbf{r_s}} \mathbf{d}_{\mathbf{z},\mathbf{k}} + \mathbf{w}_{\mathbf{z},\mathbf{n}} \tag{3-16}$$

Where $\boldsymbol{\psi}_{z,r_s}=[\boldsymbol{\psi}_{1,p,l,\psi_{2,1}}, \boldsymbol{\psi}_{2,p,l,\psi_{2,1}},\ldots,\boldsymbol{\psi}_{K_r,p,l,R_{K_r,1}}\ ]\in C^{(K_r x K_r) x M_g}$ is the sensing matrix and $\mathbf{d}_{z,\,k}=\left[\mathbf{d}_{p,1}\ \mathbf{d}_{p,2}\ldots\mathbf{d}_{p,K_r}\right]\in C^{(K_r x M_g) x 1}$ is the equivalent CIR vector of M_g antennas in one antenna group.

3.4 Compressed Sensing Based Problem

The fundamental idea behind compressed sensing theory is to use convex optimization to recover a signal that is sparse in the given region from a very small number of non-adaptive linear measurements. On the other hand, it describes how to precisely recover a high-dimensional sparse vector by lowering its dimension. From an alternative perspective, the issue can be viewed as the computation of the sparse coefficient of a signal in relation to an overcomplete system. Since random sensing matrices provide fewer non-adaptive, linear measurements, the idea of compressed sensing was mainly applied to them. These days, sparse recovery has mostly taken the place of compressed sensing. For J adjacent OFDM symbols pilots having identical pattern, we have

$$Y_{n((K_r x1)xJ)}= A_{n(((K_r x K_r) x M_g) xJ)} H_{n(((K_r x M_g) x1) xJ)} + W_{n(((K_r x1)xJ)} \tag{3-17}$$

The ψ_{z,r_s} derived in massive MIMO model fulfils the Structure Restricted Isometric Property (SRIP) condition. Precisely, SRIP can be given as

$$\sqrt{1\text{-}\delta}\ \left\|\psi_{z,\,r_s}\right\|_F \leq \left\|\psi_{z,\,r_s} d_{z,k}\right\|_F \leq\sqrt{1+\delta}\ \left\|\psi_{z,\,r_s}\right\|_F \tag{3-18}$$

Where $\delta\in[0,1)$. The definition and justification for SRIP is discussed in detail in [29]. We want to recover $\mathbf{d}_{z,k}$, where $\mathbf{y}_{z,n}$ is given. Massive MIMO channels $\tilde{\mathbf{d}}_{z,k}$ in the framework of CS theory are estimated by:

$$\hat{\mathbf{d}}= \arg\min\left\|\tilde{\mathbf{d}}_{z,k}\right\|_1 \text{ s.t. } \left\|\mathbf{y}_{z,n}\text{-}\boldsymbol{\psi}_{z,r_s}\mathbf{d}_{z,k}\right\|_2 < \epsilon \tag{3-19}$$

Where, ϵ is the noise variance. Number of algorithms can be used to solve this problem. For example, interior point methods or projected gradient methods may be used for applying convex optimization. For this purpose, orthogonal matching pursuit (OMP) is one of the famous greedy algorithms [50].

Here modified version of the OMP is applied for the CS based problem. The algorithm conventionally provides the estimate of $\mathbf{d}_{z,k}$. Furthermore, while initializing the algorithm, the sparsity level has been initiated by 1, due the fact, that in practical wireless communication scenario, having the prior information about sparsity is not possible, therefore the algorithm adaptively estimates the actual sparsity level. The algorithm further exploits the angular sparsity based on the derived model in Eq. (3-17). The algorithm provides the support of the estimated equivalent CIR vector $\widehat{\mathbf{d}}$ which also represent the ka active number users out of total Kr users.

The entire system flow, as depicted in Figure 3-3, illustrates how the chaotic sequence is integrated with the pilot data and processed for compressed sensing-based channel estimation, ultimately facilitating AUD at the base station end. This approach improves detection accuracy, especially in dense communication environments, and provides enhanced security for the massive MIMO system.

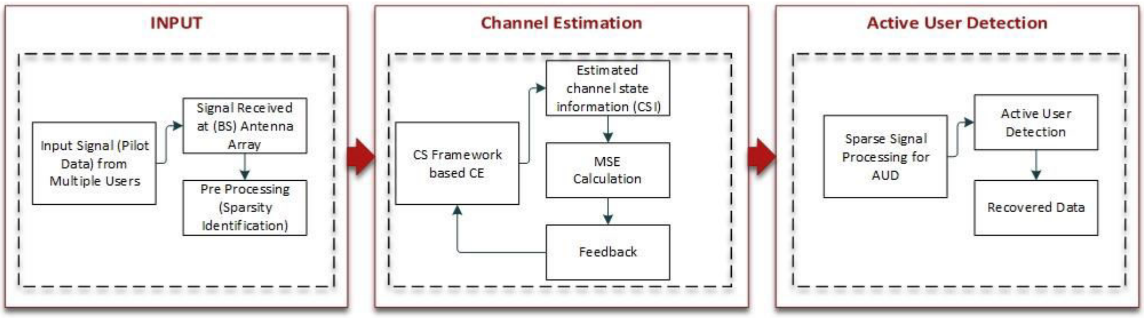

Figure 3-3: System Flow Diagram

3.5 Chaotic Sequence based Security Enhancement

Chaotic sequence is frequently being used in Digital Signal Processing because of its ability to display complex behaviour without increasing computational complexity, resulting into minimal resource usage [51].

Chaotic sequences offer lower computational overhead and simpler implementation compared to other lightweight encryption techniques, such as elliptic-curve cryptography (ECC), which makes it more suitable for resource-constrained IoT devices in B5G networks. Table 3-1 discusses the comparison of Chaotic sequence with ECC and provides the reason for use of chaotic sequence for B5G.

3.5.1 Integration of Chaotic Sequences in OMPe

The proposed algorithm (OMPe) incorporates chaotic sequences by embedding the Logistic Map generated matrix C into the sensing matrix ψ used in compressed sensing–based active user detection. Specifically, the chaotic sequence disturbs the original measurement process, making the projection of user signals onto the sensing matrix non-deterministic and highly sensitive to initial conditions. This change ensures that the residual update step in OMPe is not only driven by signal sparsity but is also randomized by the chaotic component. As a result, even if an adversary intercepts the transmitted pilots or measurement vectors, the reconstruction path followed by OMPe will differ unless the exact chaotic initialization parameters (r, x_0) are known.

Table 3-1 Comparison of Chaotic Sequences and ECC for Security in B5G Networks

Feature	Chaotic Sequences	Elliptic-Curve Cryptography
Computational Complexity	Very low, suitable for real-time use	Higher, involves modular arithmetic
Resource Requirements	Minimal (lightweight for IoT devices)	Moderate to high (may strain constrained devices)
Security Strength	Provides good randomness	Strong cryptographic guarantees

3.5.2 Logistic Map Chaotic Sequence

The Logistic Map sequence is defined by the recursive relation:

$$x_n=r.x_{n-1}.(1-x_{n-1}) \quad (3\text{-}20)$$

where: x_{n-1} is a value in the range [0, 1], r is a parameter that controls the behaviour of the map, and n is the iteration step. Where c_{ij} mapping function is used which is $\mathbf{c}_{ij}=\mathbf{x}_{\mathbf{i(n-1)+j}}$, n=1,2,3…. The Chaotic Matrix is $\mathbf{C}\in\mathbf{R}^{(K_r x K_r)xM_g}$ and $\mathbf{c}_{ij}$ is the entity in matrix C with a position of row ith and column jth.

The system enters in a chaotic environment when the values of r in the range $3.57<r\leq4$ which generates sequences that are deterministic but appear to be random. The characteristic of chaotic systems is the sensitive dependence on initial conditions, is exhibited by these sequences. Slight adjustments to the initial condition x_0 may result in considerably dissimilar sequences, which makes it ideal for purpose of pseudo randomness. The logistic map offers a further layer of randomness to compressed sensing algorithms, assisting secure the system from external factors and potential interceptors [52].

After incorporating chaotic sequence, the Eq. (3-16) becomes as follows:

$$\mathbf{y}_{\mathbf{z},\mathbf{r_s}}=(\mathbf{C}+\boldsymbol{\psi}_{z,\, r_s})\mathbf{d}_{z,k}+\mathbf{w}_{z,n} \quad (3\text{-}21)$$

$$\mathbf{y}_{\mathbf{z,r_s}}=\boldsymbol{\psi}_{z,r_s}\mathbf{d}_{z,k}+\mathbf{C}\mathbf{d}_{z,k}+\mathbf{w}_{z,n} \tag{3-22}$$

$$\mathbf{y}_{z,r_s}=\boldsymbol{\psi}_{z,\,r_s}\mathbf{d}_{z,k}+\overset{an}{\tilde{\mathbf{w}}}_{z,n} \tag{3-23}$$

Where $\overset{an}{\tilde{\mathbf{w}}}_{z,n}=\mathbf{C}\mathbf{d}_{z,k}+\mathbf{w}_{z,n}$ is the aggregate noise in the system.

3.6 Proposed Compressed Sensing Algorithm

For channel estimation an enhanced OMP algorithm is proposed that is derived from basic OMP as given in Algorithm 1.

Algorithm 1. *Orthogonal Matching Pursuit Enhanced (OMPe) Algorithm*

Step 1 (Initialization)

Inputs: Received signal: $\mathbf{y}=\mathbf{y}_{z,r_s}$, Sensing matrix: $\boldsymbol{\Psi}=\boldsymbol{\psi}_{z,r_s}$, Sparsity level: S (number of non-zero elements to recover in d), Maximum iterations for refinement: max_iter and Convergence threshold: ϵ (for adaptive refinement).

Initialize: Residual r=y, estimated signal $\hat{\mathbf{d}}=0$ of size $(K_r x M_g)x1$ and Index set I=∅

Step 2 (Iterative Process (for k=1 to S)):

Projection Step:

- Compute the projection of the residual onto the columns of Ψ: proj=$\boldsymbol{\Psi}^H r$
- Identify the index i of the column Ψ with the max absolute projection value: i=argmax $|\boldsymbol{\Psi}^H r|$

Backtracking Check

- Before adding the index, compute the estimated residual if the new index is included.
- If the new index improves the residual (reduces the norm): I=unique(I ∪ {i}) Otherwise, skip

Step 3 (Orthogonalization Improvement):

- Form the submatrix $\boldsymbol{\psi}_I$ with columns corresponding to indices in I
- Perform a QR decomposition: $\boldsymbol{\psi}_I=\mathbf{QR}$
- Solve the least squares problem using the orthogonal matrix: $\mathbf{d}_I=\mathbf{R}^{-1}\mathbf{Q}^H\mathbf{y}$
- Update the estimated signal: $\hat{\mathbf{d}}$[I]=0 (reset values to zero) then $\hat{\mathbf{d}}$[I]=$\mathbf{d}_I$
- Update the residual: r=$\mathbf{y}-\boldsymbol{\Psi}_I\mathbf{d}_I$

Step 4 (Adaptive Refinement (Iterative Refinement with Convergence Checking)):

- Refinement Loop (for each index, up to max_iter):
    - For each iteration: Re-select the submatrix $\boldsymbol{\Psi}_{\mathrm{I}}$ and solve: $\mathrm{d}_{\mathrm{I}} = \left(\boldsymbol{\Psi}_{\mathrm{I}}^{\mathrm{H}}\boldsymbol{\Psi}_{\mathrm{I}}\right)^{-1}\boldsymbol{\Psi}_{\mathrm{I}}^{\mathrm{H}}\mathbf{y}$
    - Update the residual: r=$\mathbf{y}$-$\boldsymbol{\Psi}_{\mathrm{I}}\mathbf{d}_{\mathrm{I}}$
    - Check convergence: If $\|r\|_2 < \epsilon$, terminate the iterative refinement early.
- Compute the projection and update the index set as before: proj=$\left|\boldsymbol{\Psi}^{\mathrm{H}}\mathrm{r}\right|$ and i=argmax $\left|\boldsymbol{\Psi}^{\mathrm{H}}\mathrm{r}\right|$
- If the new index I, update the index set: I=unique(I $\cup$ {i})
- Limit the index set size to S: I=I (1:S) if |I|=d_{I}

Step 5 (Final Update):

- After refinement, form the final submatrix $\boldsymbol{\Psi}_{\mathrm{I}}$: Solve for the final estimate: $\mathrm{d}_{\mathrm{I}} = \left(\boldsymbol{\Psi}_{\mathrm{I}}^{\mathrm{H}}\boldsymbol{\Psi}_{\mathrm{I}}\right)^{-1}\boldsymbol{\Psi}_{\mathrm{I}}^{\mathrm{H}}\mathbf{y}$
- Update the final estimate $\hat{\mathrm{d}}$: $\hat{\mathbf{d}}$[I]=$\mathbf{d}_{\mathrm{I}}$

Step 6 (Output):

The final output after S iterations is the estimated equivalent CIR vector $\hat{\mathbf{d}}$

The Orthogonal Matching Pursuit Enhanced (OMPe) algorithm improves sparse signal recovery by integrating adaptive refinement and improved orthogonalization methods. At the start algorithm begins with inputs including the received signal y, sensing matrix $\boldsymbol{\Psi}$, sparsity level S, maximum iterations for refinement (max_iter), and convergence threshold (ϵ). It initializes the residual r=y, the estimated signal $\hat{\mathbf{d}} = 0$, and an empty index set I.

In all the iterations until the sparsity reaches, a projection step is performed in the algorithm by computing the projection of the residual onto the columns of Ψ and maximum absolute projection value-based column is identified in the result. A backtracking check is performed before updating the I, to ensure the new index improves the residual. The index is skipped and if it is not skipped, the orthogonalizations improvement is applied after this step, where a submatrix ψ_{I} is formed using the columns with respect to I, and hence QR decomposition is performed. Estimation $\hat{\mathbf{d}}$ is estimated along with the residual by the least squares' solution.

Adaptive refinement is applied iteratively to enhance signal reconstruction after identifying S indices. In this step the least squares solution is recalculated iteratively while updating the residual and the the submatrix ψ_I is reselected. If the residual norm $||r||_2$ falls below the convergence threshold ϵ, the process terminates early. The index set I is refined, ensuring it remains unique and limited to S elements.

Finally, the final estimate of the sparse signal $\hat{\mathbf{d}}$, which is output as the estimated channel impulse response vector is calculated, using the submatrix ψ_I. By integrating backtracking checks, QR decomposition, and iterative refinement, OMPe achieves enhanced accuracy and robustness in sparse signal recovery compared to traditional OMP and OMP-IR.

Table 3-2 Comparison of Improvements in OMP

Feature	OMP	OMP IR	Enhanced OMP
Initialization	Starts with an empty support set and residual.	Similar to OMP.	Similar to OMP.
Selection of Indices	Selects index with the maximum correlation at each step.	Similar to OMP, with additional iterations for refinement.	Similar to OMP with unique indexing to avoid repetitions.
Orthogonalization	Uses standard least squares for selected indices.	Uses pseudo-inverse for better reconstruction in iterations.	Orthogonalizes to handle dimensions; zero padding before refinement.
Backtracking	Not included.	Not included; focuses on iterative refinement.	backtracking if residual does not improve.
Iterative Refinement	Not included.	Incorporates iterative refinement fully to minimize residual further.	Includes iterative refinement within a limited set of iterations.
Adaptive Refinement	Not included.	Refines iteratively with a focus on convergence and accurate index updates.	Includes convergence checks to terminate early if residuals are low.

Comparison of the features is given in Table 3-2 which summaries a comparative analysis of three variations of the OMP, OMP IR, and Enhanced OMP highlighting their unique features and functionalities for sparse signal recovery.

All three algorithms begin by initializing an empty support set and residual. This foundational step ensures a clean slate for identifying the indices corresponding to the significant signal components. While the initialization process is consistent across the three methods, it sets the stage for the differing enhancements that follow.

The original OMP selects indices based on the maximum correlation between the residual and the sensing matrix columns. This straightforward approach is retained in OMP IR and Enhanced OMP, but with slight variations. OMP IR adds iterations to refine the indices further, ensuring improved reconstruction accuracy. Enhanced OMP builds on this by incorporating unique indexing, which prevents the selection of duplicate indices, enhancing efficiency and reducing computational redundancies.

Orthogonalization plays a crucial role in signal reconstruction. OMP relies on standard least squares for the selected indices, which works well but can sometimes fall short in more complex scenarios. OMP IR addresses this by using a pseudo-inverse, a more robust method that improves reconstruction accuracy during iterative refinement. Enhanced OMP goes a step further by employing orthogonalization techniques that handle dimensional inconsistencies and utilize zero padding before refinement to ensure smooth processing and accurate results.

Backtracking distinguishes Enhanced OMP from the other two algorithms. While OMP and OMP IR do not include backtracking, Enhanced OMP introduces it as a means of verifying improvements in the residual. If the residual does not improve after an iteration, backtracking allows the algorithm to reassess and avoid suboptimal index selection, thereby enhancing accuracy.

Iterative refinement, a technique aimed at minimizing the residual further, is absent in standard OMP. OMP IR fully integrates this feature, leveraging multiple iterations to refine the selected indices and improve reconstruction. Enhanced OMP adopts this concept as well but limits the number of iterations to balance accuracy and computational efficiency.

Adaptive refinement is another feature not present in standard OMP. OMP IR incorporates iterative updates with a strong focus on convergence, ensuring the selected indices are as accurate as possible. Enhanced OMP refines this further by including convergence checks, which terminate the process early if the residual falls below a predefined threshold. This not only speeds up the algorithm but also ensures reliable results without unnecessary computations.

Conclusively, the table highlights how OMP IR and Enhanced OMP build upon the foundational OMP algorithm by introducing iterative and adaptive refinements, orthogonalization improvements, and, in the case of Enhanced OMP, advanced features like backtracking and convergence checks. These enhancements make the OMPe algorithm more suitable for complex sparse signal recovery scenarios where accuracy and efficiency are critical.

CHAPTER 4

RESULTS AND DISCUSSIONS

In this section, we present simulation results that compare the performance of OMP, OMP-IR, and OMPe in terms of CE and AUD accuracy. Simulations are carried out in different environment where various parameters are changed to check the output of the proposed algorithm and compare it with the already available algorithm. Parameter selection is listed in Table 4-1, where number of users in sub-circle are set to 32, 64 and 128, number of the active users in the sub-circle are changed i.e., 16, 24 and 32 users, number of total antennas at transmitter are set to 128, 256 and 512 keeping it according to the 2n value, number of antenna groups are changed by changing the number of antennas in a group and total number of antennas i.e., 16 and 32 where the size of antenna array was 8, 16 and 32 and the parameters are varied in two SNR scenarios i.e., 22dB and 30dB to test the algorithm in a low SNR and in another test in a high SNR environment.

Table 4-1: Parameters' Selection for Simulation

S. No.	Type	Parameter	Assigned Value
1	Users in Sub circle	Kr	32, 64, 128
2	Active Users in Sub circle	Ka	16, 24, 32
3	Total Antenna	M	128, 256, 512
4	Antenna Groups	Ng	16, 32
5	Antennas in each Group	Mg	8, 16, 32
6	QAM Type	-	16 QAM
7	System Bandwidth	B	20 MHz
8	Signal-to-Noise Ratio	SNR	22dB - 30dB
9	DFT Size	-	2048, 4096
10	Transactions	-	30

Using these parameters, the objective is to test the OMPe algorithm. Where Minimum Square Error (MSE) of CE is required to check the error in estimation results which is then compared with traditional OMP-IR. Then Active users in the sub-circle are identified, to further check test the results of joint AUD and CE. Here the objective is to compare the results of number of the identified users for different type of antenna arrays and SNR environments. To further review the average result, 30 transactions of the same settings are performed and an average result is also produced.

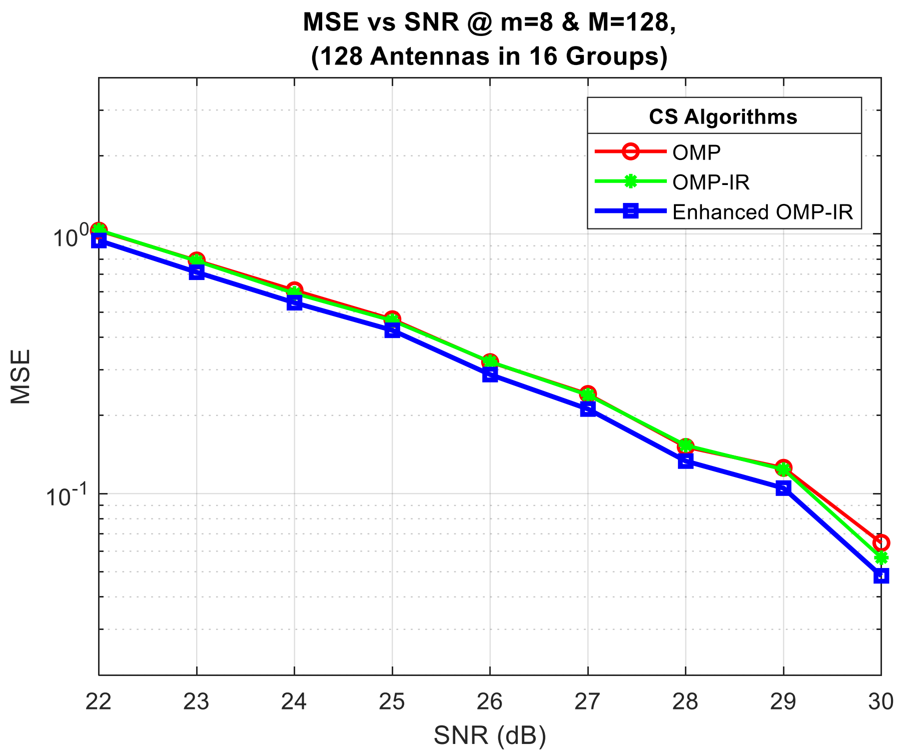

Figure 4-1 MSE Comparison at different SNRs: For m=8, M=128 and Mg=16

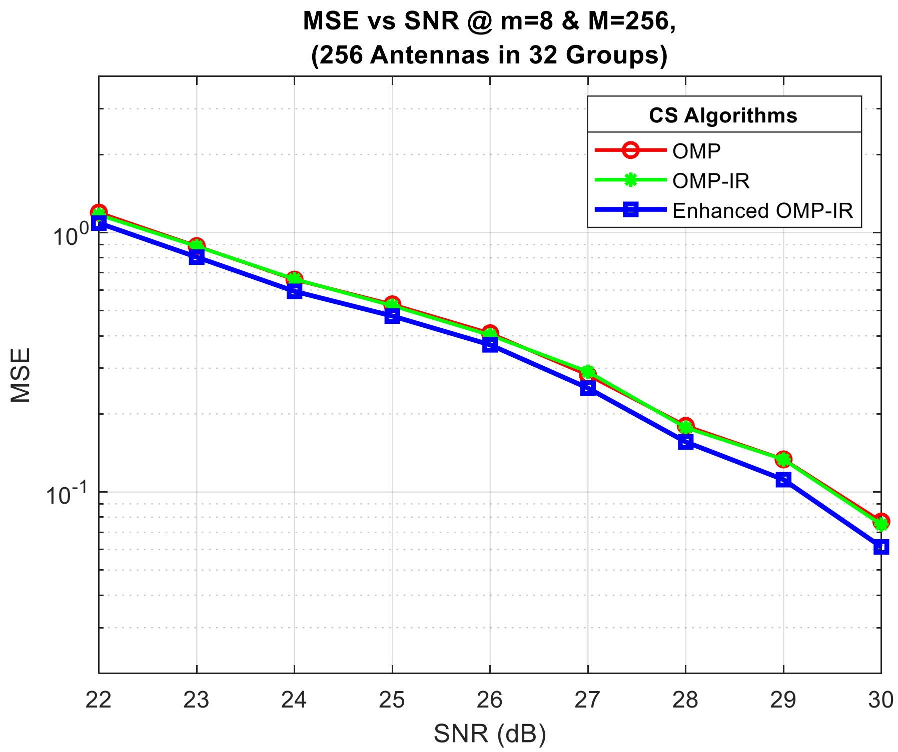

Figure 4-2: MSE Comparison at different SNRs: For m=8, M=256 and Mg=32

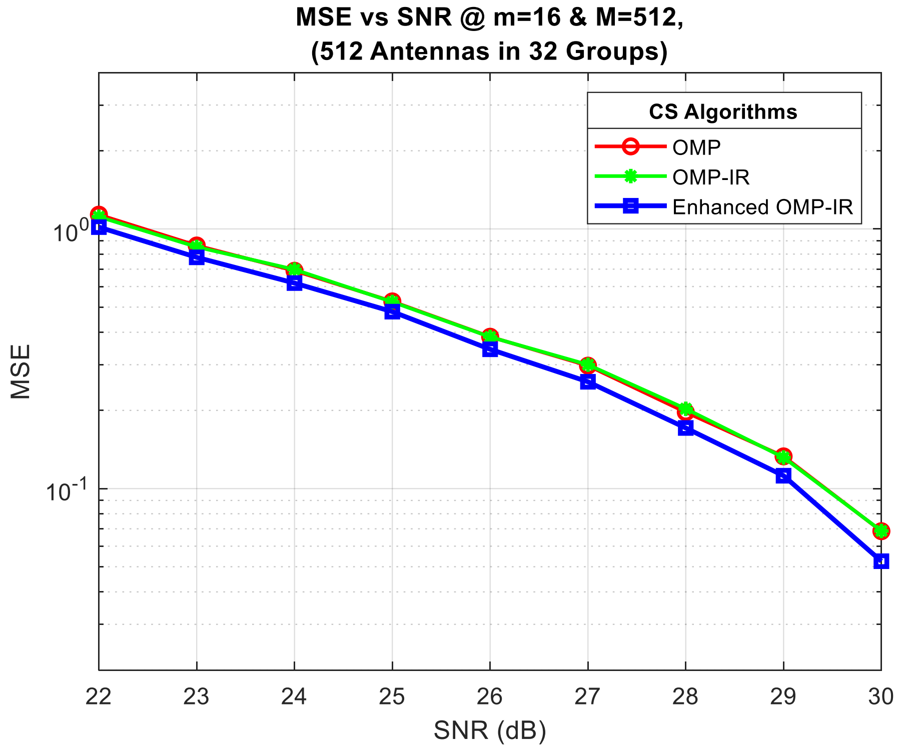

Figure 4-3: MSE Comparison at different SNRs: For m=16, M=512 and Mg=32

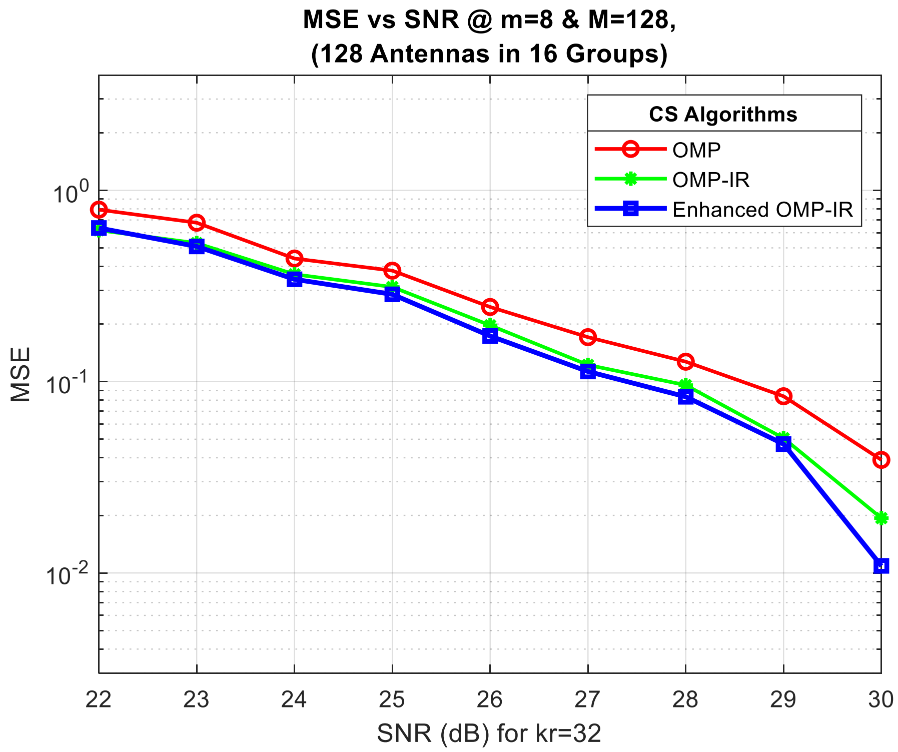

Figure 4-4: MSE Comparison at different SNRs: For m=8, M=128, Mg=16 and Kr=32

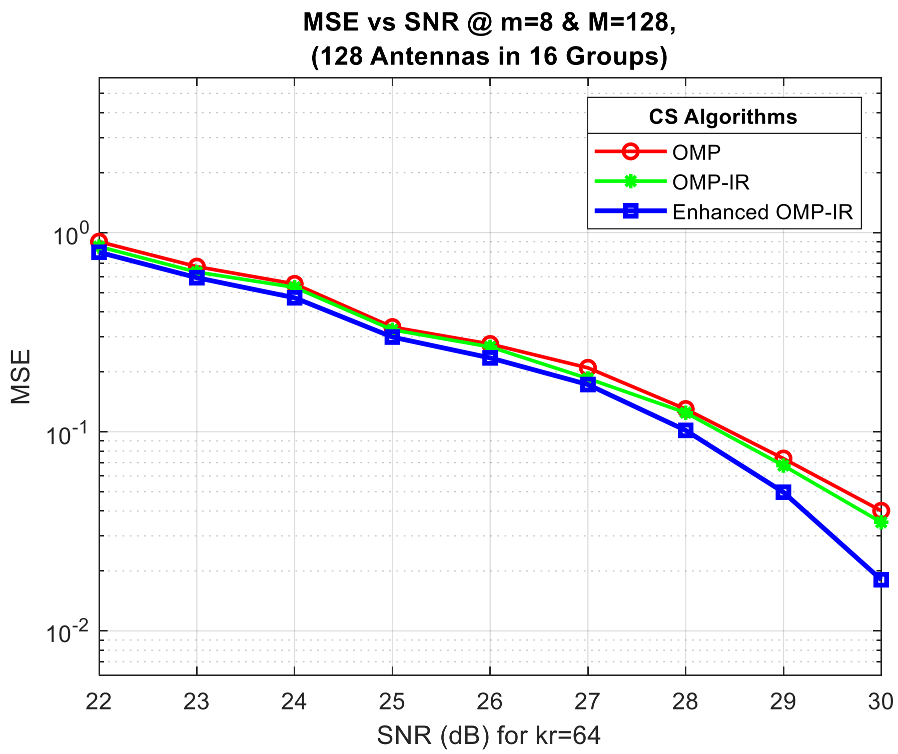

Figure 4-5: MSE Comparison at different SNRs: For m=8, M=128, Mg=16 and Kr=64

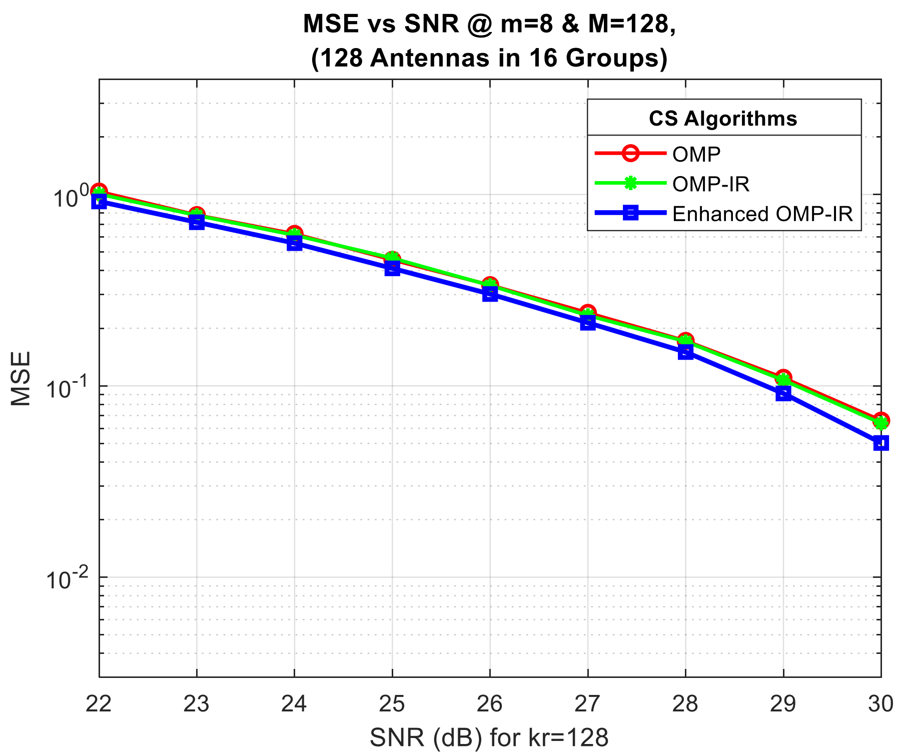

Figure 4-6: MSE Comparison different SNRs: For m=8, M=128, Mg=16 and Kr=128

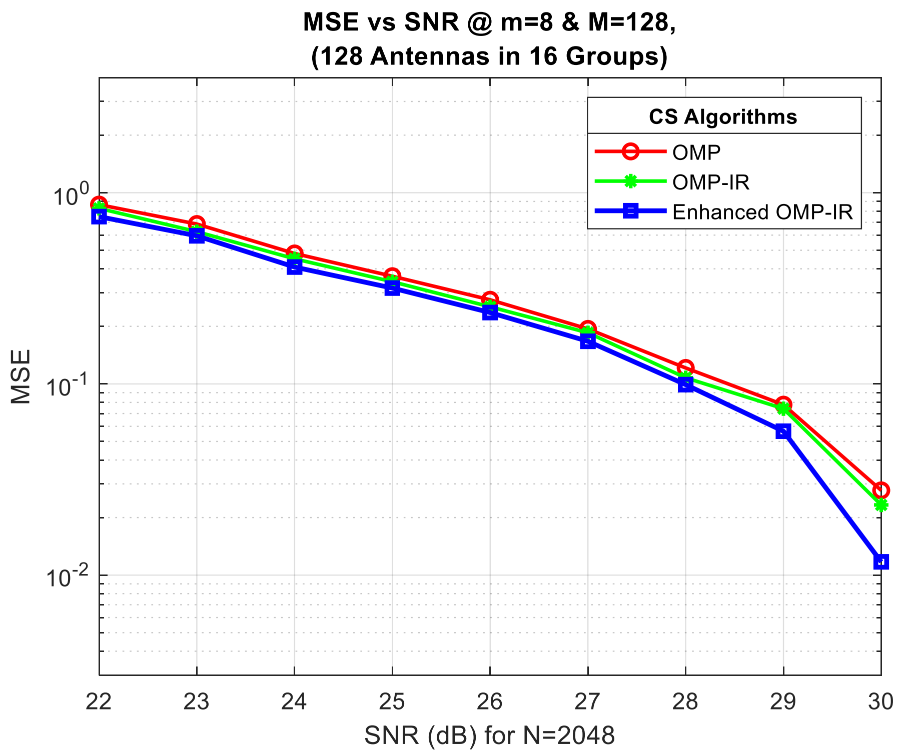

Figure 4-7: MSE Comparison at different SNRs: For m=8, M=128, Mg=16 and N=2048

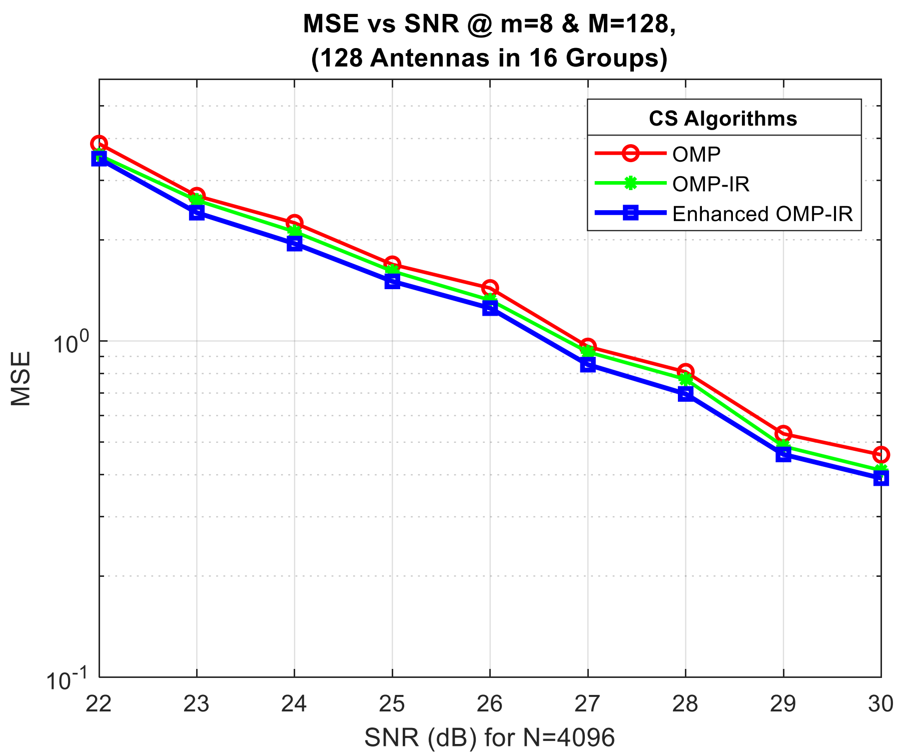

Figure 4-8: MSE Comparison at different SNRs: For m=8, M=128, Mg=16 and N=4096

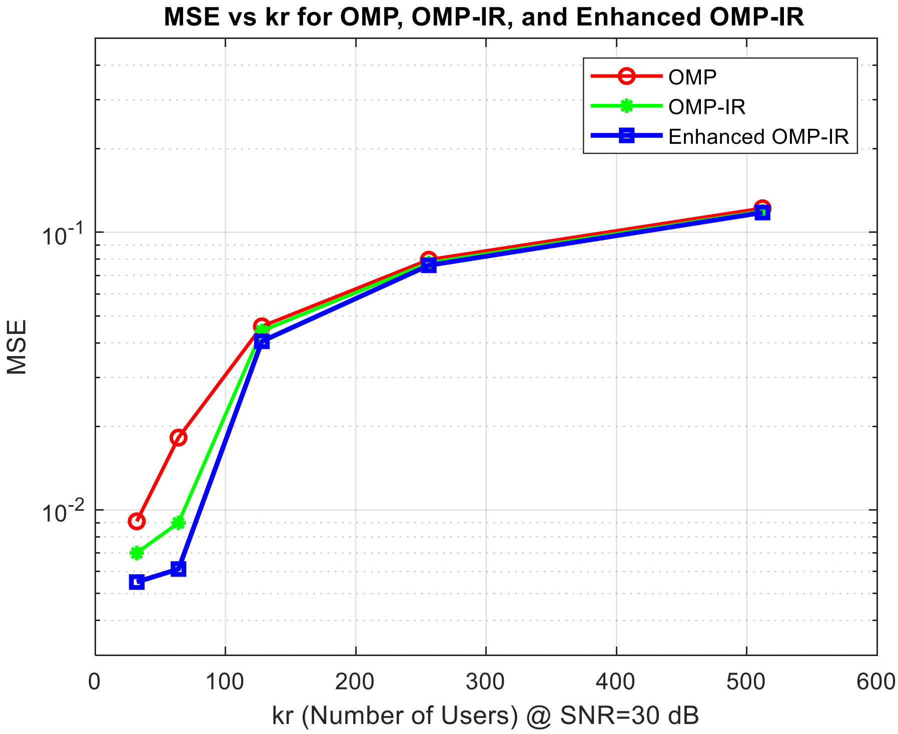

Figure 4-9: MSE Comparison for different number of users for m=8, M=128 and Mg=16

4.1 Discussion on Channel Estimation

The presented results provide a comprehensive analysis of the MSE behaviour in relation to different configurations of the OMP, OMP-IR, and OMP-enhanced algorithms for different system parameters.

4.1.1 Impact of Antenna Array Size on MSE

Figure 4-1-Figure 4-3 show MSE versus SNR for varying antenna array sizes, where M=128, 256 and 512 with a constant and variable number of antennas per group (Mg) for different configurations. It shows that there is a marginal effect on the MSE by increasing the total number of antennas, as the graphs show only a slight change. For example, at SNR = 30 dB, there is no notable degradation in performance, suggesting that the number of antennas can be increased without significantly affecting the system's error performance.

4.1.2 Effect of User Density on MSE

Figure 4-4-Figure 4-6 show the MSE behaviour when the number of users within a sub-circle Kr is increased, with m=8, M=128, and Mg=16. The findings show that increasing the user density has a minimal impact on MSE. At SNR = 22 dB, the MSE increases when the number of users is increased from Kr=32 to 128. This shows that user scaling, even at relatively high densities, does not drastically degrade the system's performance.

4.1.3 Subcarrier Effect on MSE

Figure 4-7 and Figure 4-8 demonstrate the effect of varying the number of subcarriers on MSE performance. An increase in the number of subcarriers significantly degrades the MSE performance, with higher subcarrier counts leading to more substantial degradation. For instance, at N=4096 subcarriers, the MSE is notably higher compared to N=2048. This trend suggests that a larger number of subcarriers introduce more complexity and errors in estimation, adversely affecting the overall system performance.

4.1.4 User Density and MSE Linear Relationship

Figure 4-9 shows the relationship between the number of users within a sub-circle and the MSE for a configuration with m=8, M=128, and Mg=16 having fixed SNR. The results indicate that the MSE increases almost linearly with the number of users. This means, doubling the user count leads to an increase in MSE. This linear relationship is crucial for designers as it quantifies the trade-off between user density and system performance.

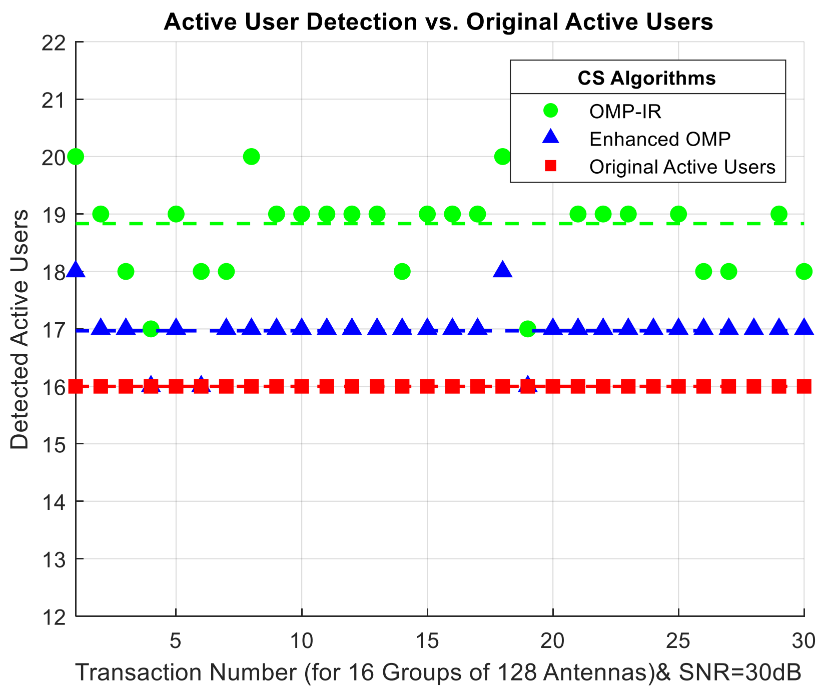

Figure 4-10: Active User Detection for 16 Groups of 8 Antennas each at SNR=30dB

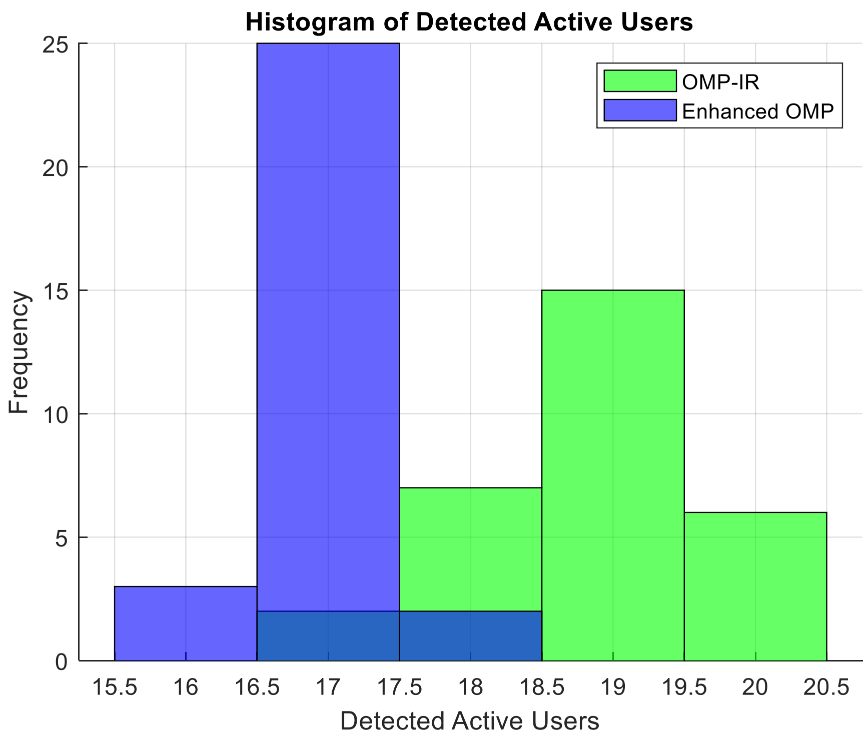

Figure 4-11: Histogram of User Identification for 16 Groups of 8 Antennas each at SNR=30dB

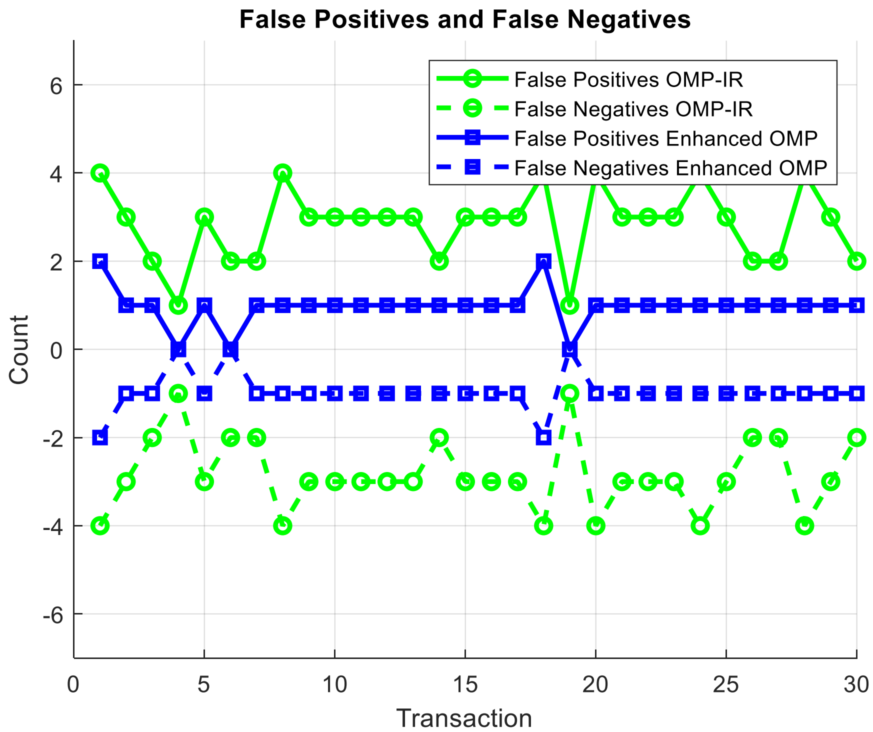

Figure 4-12: False Positives and False Negatives of User Identification

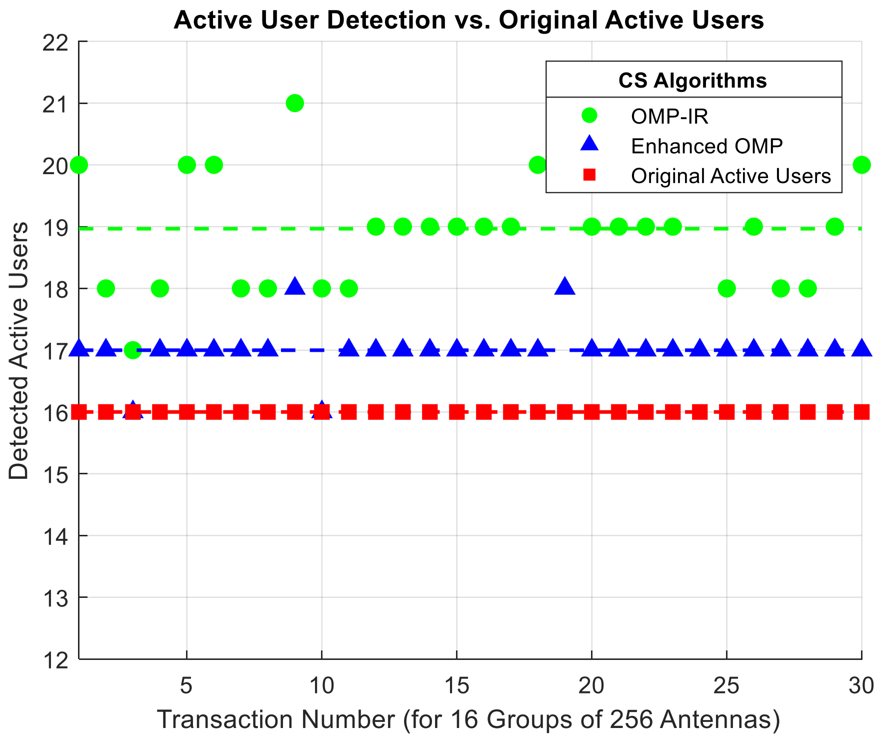

Figure 4-13: Active User Detection for 16 Groups of 16 Antennas each at SNR=30dB

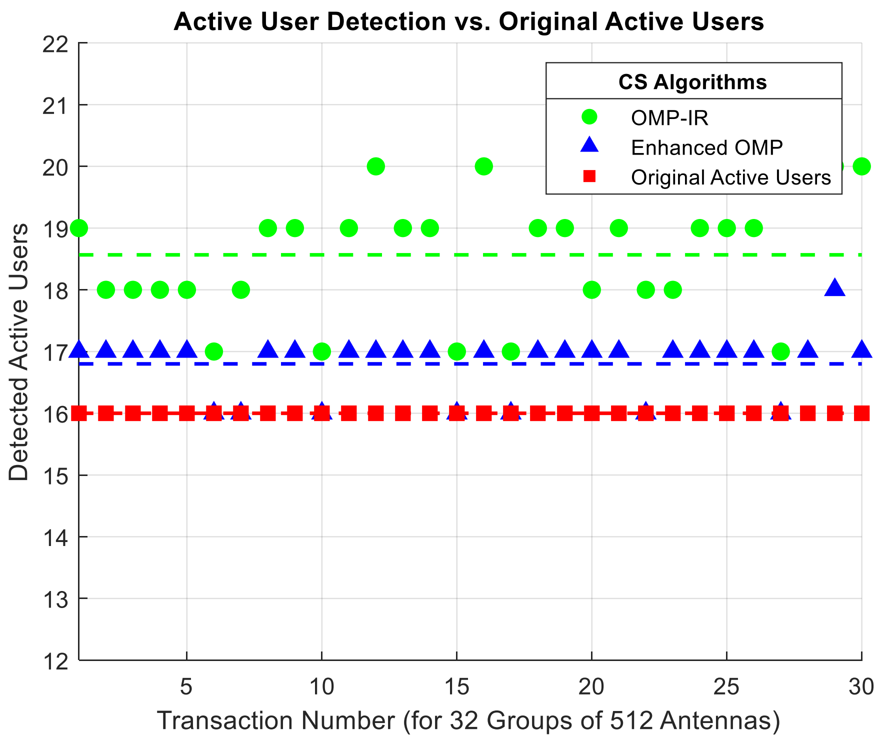

Figure 4-14: Active User Detection for 32 Groups of 16 Antennas each at SNR=30dB

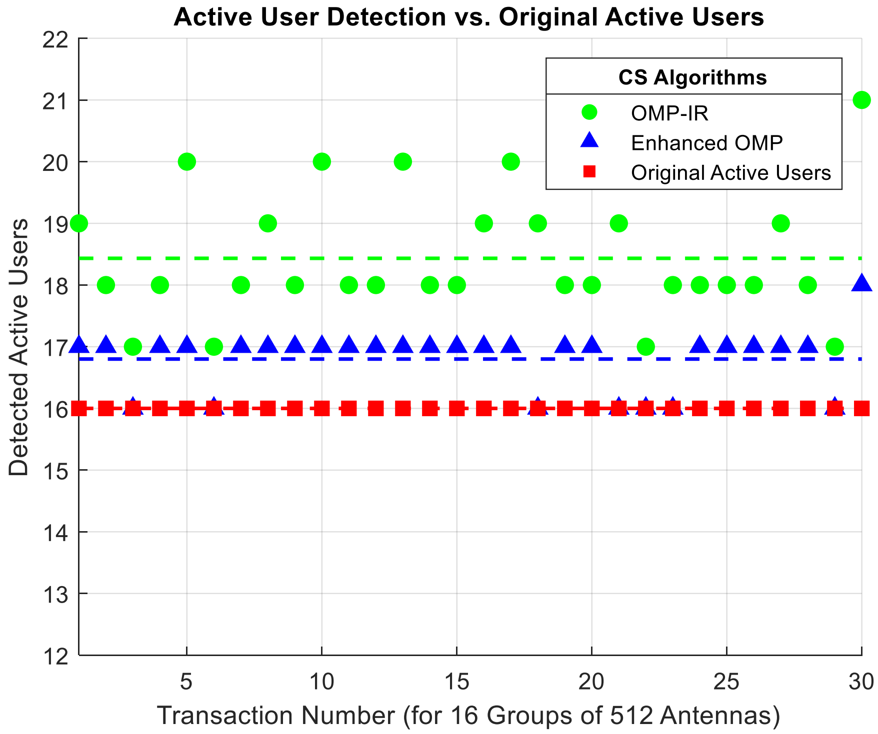

Figure 4-15: Active User Detection for 16 Groups of 32 Antennas each at SNR=30dB

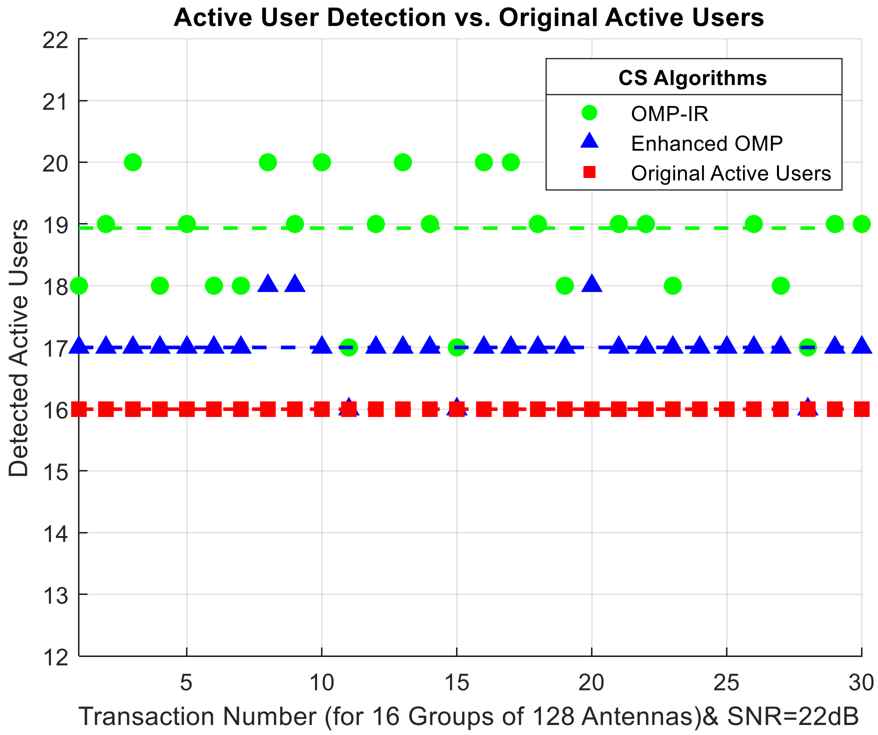

Figure 4-16: Active User Detection for 16 Groups of 8 Antennas each at SNR=22dB

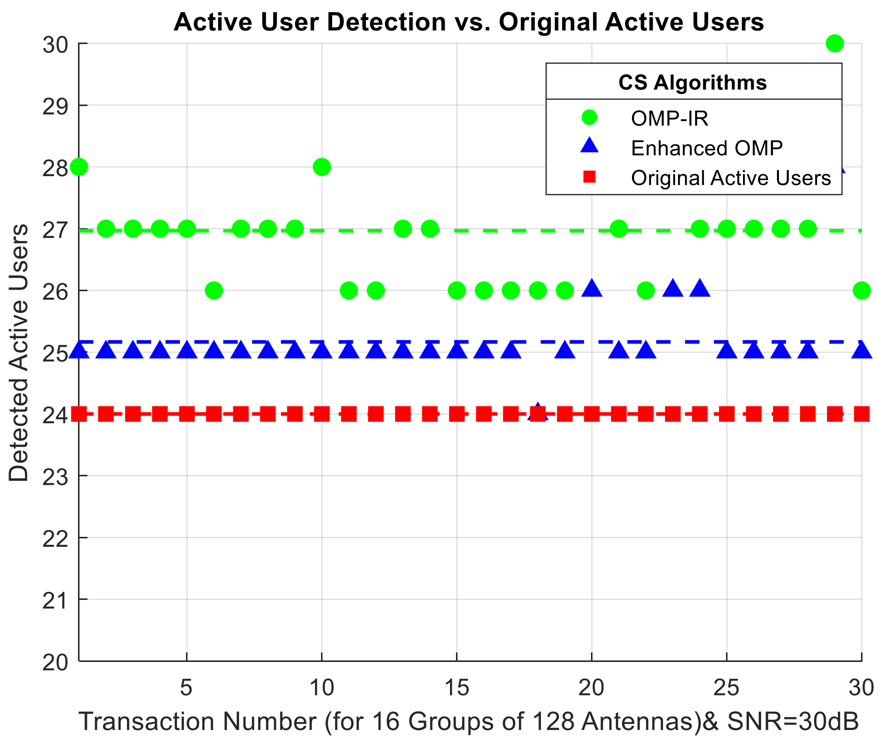

Figure 4-17: AUD for 16 Groups of 32 Antennas each @ SNR=30dB and Active Users = 24

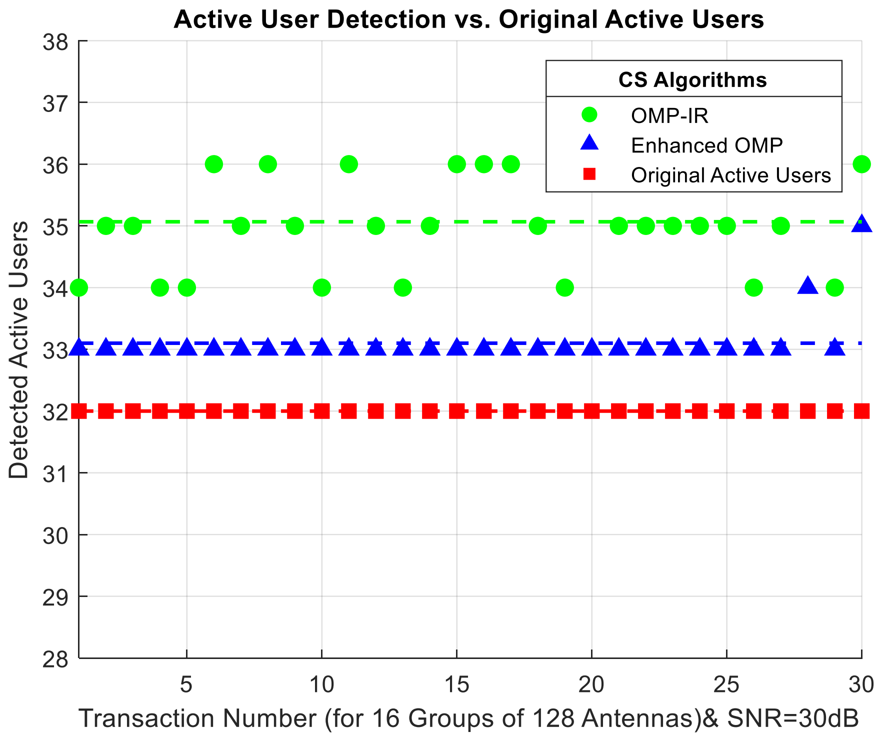

Figure 4-18: AUD for 16 Groups of 32 Antennas each @ SNR=30dB and Active Users = 32

4.2 Discussion on Active User Detection

Active user identification is simulated in Figure 4-10 presents number of identified active users using OMP-IR and OMP enhanced algorithm, in 30 repeated transactions an average of 18.85 users were identified in OMP-IR and an average of 16.95 users were identified in later algorithm. Histogram plotted in Figure 4-11 shows the number of time both the algorithms has identified the active users where blue bars represent results from proposed algorithms with and green bars show the results for OMP-IR algorithm, it is evident from the histogram that blue bars are quite closer to the actual number of active users, which can also be verified from the Figure 4-12 in which false positives (Where non active users are identified as active users) and false negatives (where active users are identified as non-active users) are plotted for 30 transactions, it is seen that the false positives and false negatives are at the lower side, quite near to the ideal line where there are no false positive or negative results, which proves the superiority of the proposed algorithm.

4.2.1 Effect of Number of Antenna Arrays and Antennas

Simulation were performed by increasing the number of antenna arrays to 16 antennas to further verify the results effect of number of antenna arrays on the AUD results, as in Figure 4-13 and to 32 as in Figure 4-14 and the results of simulations show that increasing the number of antenna arrays further improves the result and the average of AUD drops to 16.9 and then to 16.8 for proposed algorithms due to the further sparsity in angular domain. Results of increasing the number of antennas in an antenna array are also simulated in Figure 4-10, Figure 4-14 and Figure 4-15 where the number of antennas in an array are increased from 8 to 16 and then to 32 which shows further improvement in the average of AUD that has improved from 16.95 to 16.78 due to angular sparsity characteristic of the system.

4.2.2 Effect of Signal-to-Noise Ratio

To measure the performance of a communication system it is important to analyse its performance in low SNR environments because the practical wireless communication systems are prone to noise which impair the SNR of the system, Figure 4-16 simulates the system with 16 antenna groups with 8 antennas in each and a total of 128 antennas at 22dB the system is also simulated with same parameters except SNR which is 30 dB in Figure 4-10 and the average value of number of active user detection is changed from 16.95 to 17 which is very minimal impact on the result as compared to the huge change of 8dB in SNR which means that the proposed algorithm also performs well in low SNR environment.

Also, the effect of SNR can also be observed on the false positives and false negatives. At lower SNR, the system shows a slight increase in false positives, where non-active users are more likely to be misclassified as active due to noise-induced distortion, while false negatives remain relatively stable. At higher SNR, both false positives and false negatives are further reduced and the results are closer to the ideal line, demonstrating that higher SNR improves the reliability of the algorithm in distinguishing between active and inactive users.

4.2.3 Effect of Number of Active Users

In the final testing phase of simulations impact of the number of active users is very important and the same is simulated with 16, 24 and 32 number of active users in Figure 4-10, Figure 4-17 and Figure 4-18 the average number of active users slightly deviates away from the actual number of the active users but the overall difference between the actual number of active users and the average of number of identified user is not more than 1.25 which also make this algorithm suitable for dense user environments.

CHAPTER 5

CONCLUSION AND FUTURE RECOMMENDATIONS

5.1 Conclusion

In this research, we explored the problem of CE and AUD in massive MIMO systems using CS techniques. We reviewed OMP, OMP-IR, and Enhanced OMP algorithms, providing detailed mathematical insights into how they recover sparse signals. The simulation results highlight that Enhanced OMP (OMPe) consistently outperforms OMP and OMP-IR across all tested scenarios, demonstrating greater accuracy and reliability in AUD and channel estimation. OMPe maintains its superiority by closely identifying the actual number of active users, significantly reducing false positives and false negatives. This performance advantage is evident under varying conditions, including changes in the number of antennas, signal-to-noise ratio (SNR), and user density.

Simulations give valuable understandings into the effects of system parameters on MSE for compressed sensing algorithms in massive MIMO. The results show that increasing the number of antennas or users has a marginal impact on MSE, providing flexibility in system design. However, number of subcarriers should be kept in consideration to avoid any degradation in performance.

OMPe proves to be robust, particularly in challenging scenarios such as low SNR and high user density, where its detection accuracy remains stable compared to the larger deviations observed with OMP-IR. The inclusion of chaotic sequences in OMPe effectively minimizes signal correlation, further enhancing its performance. Overall, OMPe demonstrates its potential as a reliable and efficient algorithm for improving the precision of AUD and channel estimation in massive MIMO systems.

5.2 Future Recommendations

Building upon the findings presented in this research, several future directions can be explored to further enhance the performance and applicability of CE and AUD in massive MIMO systems using CS techniques:

5.2.1 Incorporation of Advanced Sparse Recovery Techniques

While the Enhanced OMP (OMPe) algorithm has shown superior results, future work can explore the integration of more advanced sparse recovery methods, such as deep learning-based approaches or hybrid algorithms. Combining machine learning with CS techniques may improve accuracy however the computational complexity will be increased. Learned Iterative Shrinkage-Thresholding Algorithm, Learned OMP and Graph Neural Networks are some of the techniques which may produce more improved results.

5.2.2 Optimization for Real-Time Systems

The computational burden of CS algorithms, especially for large-scale MIMO systems, remains a challenge. Future research should focus on optimizing OMPe for real-time processing. Hardware acceleration methods, such as GPU or FPGA implementations, can be investigated to reduce latency and improve speed.

5.2.3 Robustness under More Complex Environments

While OMPe performs well under low SNR and high user density, additional testing can be conducted in more challenging scenarios, such as high mobility environments or non-stationary channels. Future research could also investigate the impact of hardware impairments and practical signal distortions.

5.2.4 Integration with Emerging Technologies

OMPe can be extended to support emerging technologies like reconfigurable intelligent surfaces (RIS), millimetre-wave (mmWave) communication, and terahertz (THz) bands. Such integration can help address the challenges posed by higher frequencies, such as increased path loss and sparsity.

5.2.5 Enhanced Security Mechanisms

The inclusion of chaotic sequences in OMPe has demonstrated benefits in minimizing signal correlation. Future work could explore more advanced security-enhancing mechanisms, such as cryptographic techniques or secure sparse recovery, to protect against eavesdropping and other potential threats. Physical Layer Key Generation or Blockchain-Based Authentication are some of the latest techniques for exploration.

5.2.6 Scalability for Ultra-Dense Networks

With the increasing deployment of ultra-dense networks in 5G and beyond, future studies should address the scalability of OMPe.
Techniques that handle large-scale user densities and massive antenna arrays efficiently will be essential for practical deployment.

By exploring these future directions, the potential of OMPe can be further expanded, enabling it to address the evolving challenges of massive MIMO systems in 5G and beyond. These advancements will pave the way for more accurate, efficient, and scalable solutions in modern wireless communication networks.

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