# Utilization of Massive MIMO in HAPS Applications

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***Abstract*—Low earth orbit (LEO) satellites or high-altitude platform stations (HAPS) suffer from a myriad of problems in the field of wireless communications. Some of these major difficulties include problems such as long propagation delays, mutable channel state information due to the mobility of both the ground station and the transmitter, excessive computational complexity for signal processing, the Doppler shift, and delays which have to be compensated. With growing demands of the fifth-generation protocols for cellular networks (5G) and the ongoing research of the sixth-generation standards for cellular network (6G) applications, topics such as spatial diversity and spatial multiplexing become more relevant than ever. Furthermore, frequency reuse (FR) strategies and space-angle based user grouping (SAUG) will be vital as the number of smart devices that the average person uses grows. For optimizing all these concepts and addressing all these problems, massive MIMO (Multiple Input Multiple Output) systems should be utilized. With device usage growth, managing and mitigating interference is expected to become a substantial conundrum. As a result, massive MIMO signal processing is an important effective tool in maximizing gain and minimizing interference, making it an ideal application for the downlink and uplink between a HAPS and the ground station. This paper focuses on adapting a massive MIMO model built specifically for HAPS via MATLAB with some parameters like free-space path loss (FSPL), downlink precoding, Rayleigh/Rician fading, beamforming, and SAUG considered for the sake of improving the model. The results showed successful receiving of the transmitted signal. Furthermore, several pairs of parameters for massive MIMO systems were compared including: zero-force (ZF) versus minimum mean square errors (MMSE) precoding techniques, line of sight (LOS) versus non-line of sight (NLOS) cases, as well as massive MIMO-based LEO satellite versus massive MIMO HAPS system. The massive MIMO HAPS system showed favorable qualities for both LOS and NLOS scenarios in terms of bit error rate (BER) performance metrics to that of the LEO satellite especially when paired with MMSE precoding techniques and a greater number of antennas in the receiving antenna array.**

***Index Terms*—High Altitude Platform Station, HAPS, LEO, Wireless Communications, Massive MIMO, MIMO, Multiple Input Multiple Output, Signal Processing, Gain, Interference, 5G, Doppler, MATLAB, Non-terrestrial.**

## I. Introduction and Motivation

As the utilization of devices based on the fifth-generation protocols for cellular communication networks (5G) continue to surge, ensuring the attainment of necessary data rates has become an even more pressing concern [2]. This is particularly evident in non-terrestrial communications, where interference and noise pose significant obstacles. HAPS, positioned at approximately 20 kilometers above the Earth's surface, is a prominent non-terrestrial network facing challenges in achieving real-time due to long-distance communication based on the high altitude, propagation delays, and ground station mobility. The implementation of super macro-base station technology adds to the complexity, as the discrepancy in the number of ground-based base stations amplifies the challenge.

## II. Objective

This project is focused on developing a specialized massive MIMO model with precoding, beamforming, and channel state information, tailored for HAPS communication. This research also involves an analysis to bridge the fundamental differences between LEO satellites and HAPS, considering factors such as altitude, propagation characteristics, Doppler shift, and delay compensation. Furthermore, this project aims to determine and optimize the most suitable frequency reuse schemes for HAPS communication networks. Additionally, one goal of the project is to assess the quality of the output signal from various precoding methods such as ZF and MMSE. With this goal, the most effective precoding technique can be identified for HAPS-assisted MIMO communication systems. Another goal of the project is to determine the differences in BER of massive MIMO systems of HAPS vs current LEO applications.

## III. Novelty/Expected Results

The expected outcome of this project is to showcase the techniques that would characterize a significant improvement in signal processing performance for HAPS communication, leading to increased data transmission rates and reduced interference. As such, there would be enhanced precision in channel state information estimation, enabling more efficient utilization of communication resources. The research also anticipates amplified capacity and quality of service for HAPS networks, ultimately resulting in superior user experiences across a variety of applications, spanning from IoT devices to high-bandwidth data transmission. By addressing specific challenges and optimizing key parameters, the goal of the project is to achieve a significant improvement in signal processing performance and interference mitigation for HAPS-assisted communication systems. The bit error rate graph should be expected to have a downward trend on a logarithmic scale. Furthermore, another expected result would be that the number of receiving base station antennas should increase if the number of users grows. For the LEO satellite versus HAPS cases, there should be a higher BER present for LEO satellite cases versus that of the HAPS case.

## IV. Contributions

This undertaking holds the potential to substantially enhance the integration of massive MIMO technology into non-terrestrial communication systems. The principal contribution lies in the presentation of graphical representations elucidating what the BER value is relative to the Eb/No for a varying number of receiver antennas for both HAPS and LEO cases. As such, this project directly compares the performance of a massive MIMO system, undergoing both ZF and MMSE precoding techniques, on a LEO satellite versus that on a HAPS. These results can bolster and enhance signal processing capabilities, especially when paired with the fact that they also show how the massive MIMO changes for NLOS applications in urban settings and LOS capabilities in rural scenarios. With the unique SAUG algorithm developed based on angle threshold and the model's adaptability in non-terrestrial communication systems, this project can have a profound impact on the advancement of HAPS technology and its applications.

The steps for these contributions start with the optimization of wireless communications which involves the development and application of a channel matrix model. By adopting such a model, numerous benefits can be realized, encompassing a reduction for frequent updates for downlink precoding, uplink receiving, and user grouping. While devising this model framework, it is noteworthy to recognize that certain adaptations and modifications must be undertaken when transitioning from the model for LEO satellites [1] to that of HAPS.

Additionally, the fundamental differences between LEO satellites and HAPS are acknowledged. LEO satellites are inherently mobile and require periodic re-boosting [1] due to orbital decay, unlike stationary HAPS positioned at approximately 20 kilometers above the Earth's surface. The lower altitude of HAPS than that of LEO satellites also makes the channel require less delay compensation.

Second of all, the signal propagation characteristics intrinsic to LEO satellites must be adjusted to align with the specific attributes of HAPS. Notably, HAPS remain stationary in most cases, in contrast to the continuous motion characterizing LEO satellites, resulting in a Doppler shift [3] dependent on the mobility of the user terminal.

Additionally, a ray-tracing model can be used to estimate the complex baseband DL space domain channel response between the HAPS and the user terminal at a certain time and frequency. Furthermore, some limiting constraints must be addressed such as the time interval or how fast does the channel matrix model vary for HAPS.

While in a LEO satellite, all propagation paths' angles for the same user terminal are approximately identical. However, HAPS is at a lot lower elevation than a LEO satellite so this is a limiting factor that must be examined to see if the underlying assumptions for MIMO communications in a LEO satellite would match that of a HAPS satellite. Another critical aspect that requires thoughtful consideration is determining the most optimal frequency reuse scheme pertaining to the HAPS communication network as the separation for using FR4 may not be optimal in HAPS as it is in LEO applications.

## V. Articles Of Innovative Design

Article [3] investigates the benefits of using a triangular lattice array over a square one in 5G massive MIMO systems for HAPS. Analyzing a planar array with 64 elements, the study compares triangular and square lattice arrays in terms of array gain, ASLL, and mutual coupling. Emphasis is on the system-level impact, evaluating SE and SIR. The researchers propose a new beamforming technique that optimizes the antenna array geometry and improves the system's capacity. Results indicate superior performance of the triangular lattice array, making it appealing for 5G massive MIMO applications. Article [4] proposes a new user grouping scheme for HAPS-incorporated massive MIMO systems, utilizing statistical-eigenmode (SE). The proposed Fubini-Study distance-based modified K-means (FS-MKM) algorithm aims to reduce intra-group interference and enhance system performance. The modified K-means algorithm improves the initial point selection of the original K-means. The study focuses on addressing challenges in massive MIMO systems on HAPS, such as feedback complexity and delays due to the HAPS's altitude. Simulation results demonstrated significant performance improvements with the proposed user grouping algorithm.

## VI. Mathematics Behind MIMO

To dive into the mathematics behind MIMO, one has to start with equation 1. This equation shows how to represent an output signal received by a receiver antenna that was initially engendered by a transmitter antenna, where H represents the channel model, x represents the input signal, and n represents the noise.

$$y = \mathrm{Hx} + \mathrm{n} \tag{1}$$

Equation 1 can be adjusted for a MIMO scenario with a maximum "Nr" number of receiving antennas and a maximum "Nt" number of transmitting antennas. Illustrated in equation 2, the output signal, input signal, and noise can be represented as a vector whereas the channel model H would be depicted by a matrix [7] that serves to process the signal of each transmitting antenna into an impulse response.

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix} = \begin{bmatrix} h_{1,1} & h_{2,1} & \ldots & h_{Nt,1} \\ h_{1,2} & h_{2,2} & \ldots & h_{Nt,2} \\ h_{1,3} & h_{2,3} & \ldots & h_{Nt,3} \\ \ldots & \ldots & \ldots & \ldots \\ h_{1,Nt} & h_{2,Nt} & \ldots & h_{Nt,Nt} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \ldots \\ x_{Nt} \end{bmatrix} + \begin{bmatrix} n_1 \\ n_2 \\ \ldots \\ n_{Nt} \end{bmatrix} \tag{2}$$

Using matrices for channel modeling and vectors for input, output, and received signals is a common approach in MIMO systems. However, it comes with some disadvantages. Matrices can become large and computationally demanding, especially when dealing with numerous antennas, which can strain computational resources and memory. Additionally, matrix operations, like inversions, are frequently employed in MIMO signal processing and can be computationally intensive and potentially unstable [7]. Another challenge is the dimensionality of MIMO systems, which increases with the number of antennas, making it harder to understand and program, particularly in larger setups. Balancing model fidelity and computational efficiency is a dilemma. Larger matrices provide accuracy but demand more computational resources, leading to performance trade-offs. Hardware capabilities play a crucial role; not all platforms efficiently handle matrix operations, necessitating specialized hardware or software optimizations. Scalability is vital as MIMO systems evolve, requiring adjustments to accommodate a growing number of antennas. In real-time MIMO systems, latency can be a concern due to the computational demands of matrix operations. This is a critical problem with more massive MIMO applications.

For a geostationary HAPs, downlink precoding assumes a crucial role in ensuring efficient and reliable signal propagation over large distances. Due to the inherent high path loss at such altitudes, as dictated by the inverse square law, optimizing the transmitted signal using downlink precoding becomes indispensable [7]. Down- link precoding can combat signal attenuation and shadowing effects, enabling the efficient allocation of power and resources to user equipment, thereby enhancing the overall coverage and capacity of the communication link [8]. The use of downlink precoding in geostationary HAPs systems also provides resilience against fading caused by multipath propagation [9]. By exploiting spatial diversity through precoding, the system can mitigate adverse effects such as signal distortion, inter-symbol interference, and multipath fading, resulting in improved link quality, reduced error rates, and reliable communication [10]. Furthermore, downlink precoding techniques can effectively combat interferences caused by neighboring HAPs operating in adjacent frequency bands or nearby cells [11].

Zero-force is a type of precoding technique done on the receiving signal to eliminate interference. It mitigates interference by shaping transmitted signals to nullify interference at the receiver. Equation three shows how one person can do zero-force precoding with an inversion matrix. In equation 3, H signifies the transpose of the channel matrix "$H^T$" The transpose operation rearranges the rows and columns of "H," effectively converting its rows into columns and vice versa. The term "$(H^TH)^{-1}$" represents the inverse of the product of the transpose of the channel matrix and the original channel matrix. This inversion operation is central to the zero-forcing precoding technique, as it enables the adjustment of transmitted signals to reduce interference and improve signal reception.

$$W = (H^T \cdot H)^{-1} \cdot H^T \tag{3}$$

The MMSE decoder was developed to address the problem of ignoring noise in the zero-forcing decoder, which can lead to reduced performance in cases with low signal-to-noise ratio. By incorporating the effect of noise on the received signal, the MMSE decoder aims to provide better results than traditional zero forcing techniques in cases where the noise of a signal is high relative to the signal. Equation 4 shows the MMSE equation to be used in conjunction with cases that feature low signal to noise ratio. Note that the term I represents the identity matrix.

$$\left[W_{MMSE} = (H^T \cdot H) + I * \tfrac{1}{SNR}\right]^{-1} \cdot H^T \tag{4}$$

After precoding is done, beamforming is performed, which is a signal processing technique that is characterized by the ability to intricately manipulate the phase and amplitude of signals across an array of antenna elements, thereby facilitating the creation of a highly focused and directional "beam" of electromagnetic energy [12].

## VII. Developing a Model

The methodology for developing a massive MIMO MATLAB model customized for HAPS represents a systematic and scholarly approach to the modeling and analysis of wireless communication systems in the specific context of high-altitude platforms. In response to this growing interest of HAPS, a massive MIMO system tailored to the demands of HAPS holds the key to augmenting communication reliability and spectral efficiency. Given this importance in reliability, two models are developed in this paper, and the MATLAB codes for both models have been provided in a github repository referenced under [19].

The first model is a model for assessing how a massive MIMO on a HAPS compares to a massive MIMO on a LEO satellite in both NLOS and LOS cases using binary phase shift keying (BPSK) modulation scheme encoding techniques. BPSK was preferred over quadrature amplitude modulation (QAM) because of its low cost and complexity [18]. Furthermore, even though QAM can attain higher data rates compared to BPSK by employing a greater number of signal points and transmitting more bits per symbol, it demands a wider bandwidth compared to BPSK due to the proximity of signal points, necessitating greater separation to prevent interference. Finally, QAM exhibits lower power efficiency than PSK since it consumes additional energy in modulating both amplitude and phase.

To address the channel matrix model (H) for the NLOS case, a probabilistic model with complex Gaussian realization of mean 0 and a variance of 0.5 per dimension is used. A complex Gaussian distribution is common in NLOS models because it is often a valid approximation for the effects of multiple reflections and scattering in a wireless environment. Assuming a mean of 0 is often reasonable in NLOS scenarios, where the direct path between the transmitter and receiver is obstructed, and the received signal is composed of multiple scattered and reflected paths. In such cases, the contributions from various paths may sum up to an average of zero. The variance of 0.5 per dimension was chosen based on statistical characteristics from uncertainties associated with the complex channel coefficients as they are are independent. This probabilistic model ensures attainment of the statistical channel state information. The channel response is considered to be a combination of multiple scattered paths with random phases and amplitudes. The magnitude of the sum of these paths follows a Rayleigh distribution, while the phases are uniformly distributed. For the channel matrix model for the LOS scenario, an approximation stemming from the geometry of a uniform linear antenna array and the distribution of users was utilized [14].

Following the basic parameter definitions, in both the NLOS and LOS cases of the LEO satellite's massive MIMO model, Doppler shifting is incorporated with FSPL and factored into the channel matrix followed by the addition of additive white Gaussian noise (AWGN) subsequently followed by ZF or

MMSE precoding. Multiple iterations are used to obtain and average out the results.

The second model is a signal processing model for generating a random signal and passing it through an array of transmitting antennas downstream with a massive MIMO channel, where it will experience a free-space path loss, delay compensation, Rician fading, various downlink precoding techniques [8], and beamforming to transmit the signal successfully to a groups of users where the users are grouped together based on their spatial angles. The core components of this methodology encompass path loss modeling, MIMO channel modeling, advanced precoding and beamforming techniques, spatial-based user grouping, and considerations for frequency reuse.

To begin the development of the model, the number of transmitter and receiver antennas has to be defined. For a massive MIMO application, this usually involves having over 16 x 16 antennas. Additionally, the carrier frequency and altitude play a role as a significant parameter in the subsequent calculation of the free-space path loss, since this computation directly hinges upon the chosen carrier frequency and the altitude of the HAPS.

Path loss modeling accounts for the unique attributes of HAPS, including their altitude, carrier frequency, and the spatial separation between the HAPS-based transmitter and ground-based receivers. This model serves as the foundational element for designing communication systems in the HAPS environment, ensuring the accuracy of link budget calculations and reliable connectivity. MIMO channel modeling further refines the methodology by encapsulating the wireless link dynamics between the HAPS and ground-based receivers. This involves specifying parameters such as the number of antennas at both ends, path delays, and variations in channel gain. The choice of an appropriate fading model, such as Rician fading, aligns the model with the real-world intricacies of wireless channels at high altitudes. In addition, the implementation of advanced precoding techniques, including MMSE and ZF precoding, along with beamforming [13], optimizes the transmission of data streams from the HAPS to multiple ground-based users.

These techniques are essential for interference mitigation and signal quality enhancement in this unique environment. Spatial-based user grouping and the concept of frequency reuse play a pivotal role in enhancing spectral efficiency, as they allow for resource allocation to ground-based users while mitigating interference. The consideration of frequency reuse strategies maximizes network capacity while ensuring acceptable signal quality. Collectively, this methodological framework, combined with the provided MATLAB code, allows pairing of a massive MIMO system with HAPS. To start the actual algorithm and design, the flowchart for the algorithm is illustrated in Figure 1.

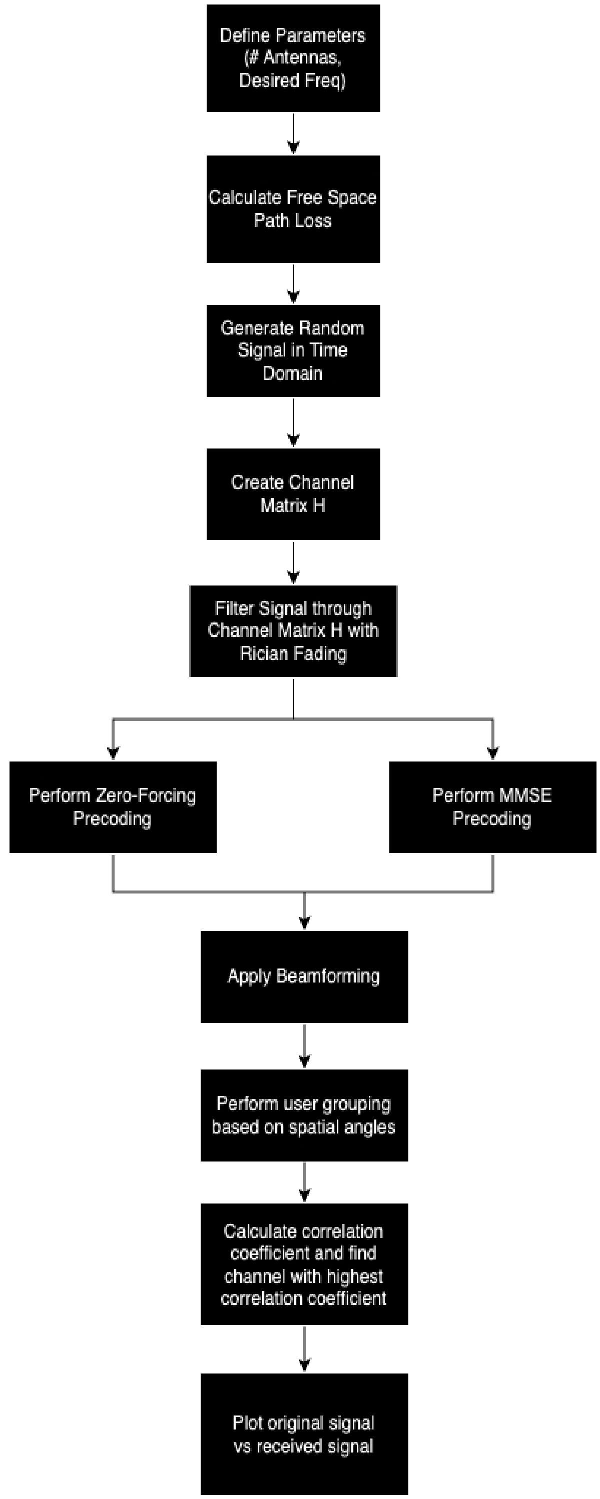


Fig. 1: Algorithm for massive MIMO, precoding, beamforming, and SAUG

The choice of 3 GHz exemplifies a practical millimeter-wave frequency, commonly employed in HAPS to enable high data throughput and limited interference. The resulting path loss (L) signifies the signal attenuation over distance and forms the basis for understanding the signal strength in this wireless environment. The signal length represents the temporal extent of the transmitted signal, and the sampling rate, set at 1 MHz, demarcates the signal's discretization in time. The prescribed coverage radius, a critical facet for modeling the communication range of the HAPS, is set to 50 kilometers.

In terms of signal generation, the random signal matrix is generated to emulate the data transmitted from the antennas. This randomness reflects real-world signal variability, incorporating a wide array of potential data patterns. The crux of the code revolves around channel modeling. It uses a 'comm.MIMOChannel' object, incorporating critical aspects like path delays, average path gains, and fading distribution. Notably, the choice of a Rayleigh fading distribution is significant, as it aptly models NLOS conditions often encountered in urban areas. In urban environments, signals tend to exhibit both a non-line-of-sight component and multiple scattered signals, which Rayleigh fading captures. This choice facilitates a more realistic representation of urban wireless communication scenarios. Additionally, the option for Doppler shifting is included, but for a geostationary HAPS as used in this model, there is no Doppler shifting. Following channel modeling, the code introduces ZF precoding and MMSE precoding, instrumental in mitigating interference and optimizing signal quality. The zero-forcing and MMSE precoding matrices are computed and applied to the transmitted signal. Additionally, beamforming, exemplified with a beamforming matrix (B) based on a specified angle, allows steering signals in desired directions, catering to specific communication needs. SAUG is then simulated, a process vital in scenarios necessitating efficient resource allocation and user grouping. The code examines spatial angles between users to group those within a defined angle threshold, which aligns with real-world requirements.

To assess the quality of the received signal, the code computes correlation coefficients between the original random signal and the signal after Rayleigh/Rician fading. This offers insights into how well the received signal matches the transmitted signal, crucial in evaluating the reliability and fidelity of the communication system. Finally, signal plotting provides a visual dimension to signal analysis. The original random signal and the received signal post-beamforming are graphically represented, aiding in the visual comprehension of signal transformation and behavior.

## VIII. Results and Analysis

The results for the first model highlight and compare the performance metrics in terms of BER and various normalized signal-to-noise ratios for massive MIMO systems incorporated on HAPS versus those installed on LEO satellites. The varying number of receiver antennas is also a significant indicator of the BER in that the greater the number of receiving antennas is in the phased antenna array, the less the BER would be due to improved beamforming characteristics.

The plots for the BER versus the number of receiving antennas for a massive MIMO on both LEO and HAPS are shown in Figures 2 through 5. These figures illustrate that the massive MIMO systems for LEO have a slightly higher BER on average than for HAPS. Due to there only being a slight difference, the assessment of the model should be questioned, including the modulation scheme for encoding data. If a differential quadrature phase-shift keyring (DQPSK) is used, the accuracy of the results might increase dramatically as there is more phase synchronization between the transmitter and receiver with the phase difference between adjacent symbols [18]. These issues could also stem from the fact that the channel matrix models are being estimated from a Gaussian

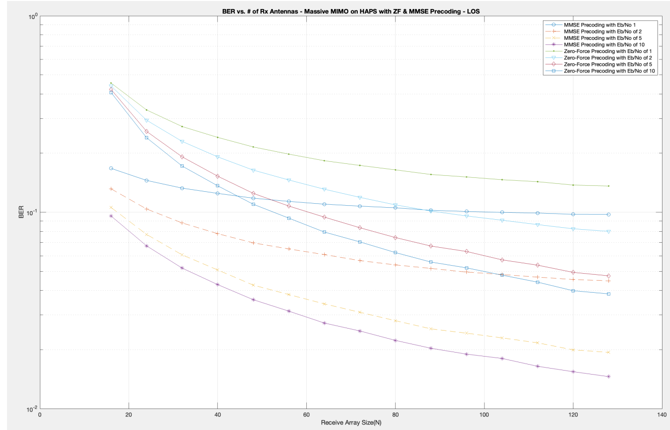


Fig. 2: BER vs. receiver antenna array size using LOS scenario for HAPS

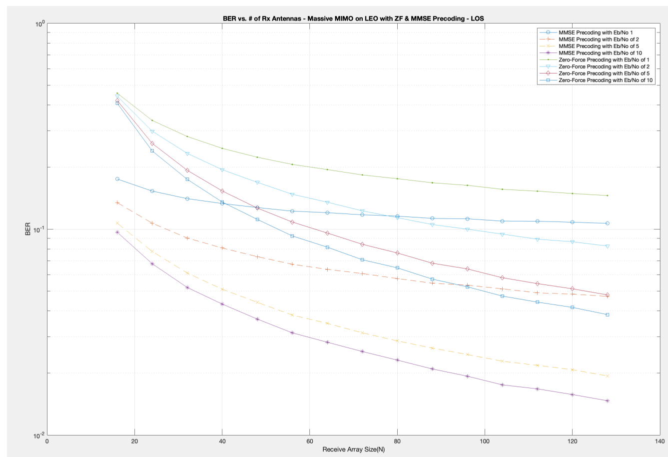


Fig. 3: BER vs. receiver antenna array size using LOS scenario for LEO satellites

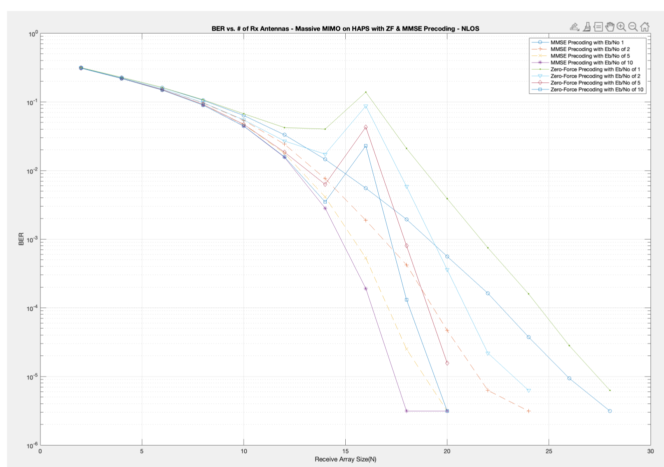


Fig. 4: BER vs. receiver antenna array size using NLOS scenario for HAPS

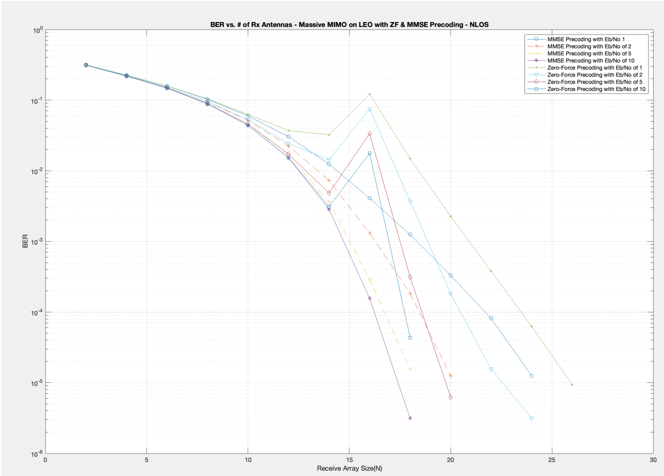


Fig. 5: BER vs. receiver antenna array size using LOS scenario for LEO satellites

distribution model for NLOS cases and the geometry of a linear array for LOS scenarios. Additionally, massive MIMO systems with more than fourteen receiving antennas show lower BER with MMSE precoding technique than those with ZF precoding technique.

While the NLOS condition assumes a scattering environment, leading to increased multiplexing gain (dependent on the rank of the channel matrix H), its signal-to-noise ratio (SNR) consistently remains lower due to factors such as reflection, diffraction, and scattering loss. To enable a meaningful comparison between line-of-sight (LOS) and NLOS cases, it becomes necessary to adjust the SNR downward for the NLOS scenario. Simulation results indicate that a reduction of approximately 25 dB in SNR for the NLOS case is required to achieve similar bit error rate (BER) performance as the LOS case. Additionally, the FSPL incorporated represents a numeric alteration in the signal strength as it propagates through space, while the signal itself undergoes a binary change. This discrepancy in nature raises concerns about potential issues in the fidelity of data transmission, as the numeric variations introduced by FSPL may not align seamlessly with the binary nature of the signal, possibly leading to challenges in accurately preserving and decoding the data.

```
User Groups:
Group 1: Users 1   6   8  12  14  19  20  22  28  30  33  34  38  40  41  42  44  45  47  49  51  56  57  62  63  66  67  68  71  72  74  77  82  87  88  89  90  98
Group 2: Users 2   4  16  29  50  59  73  96  97
Group 3: Users 3   5   7   9  10  11  13  15  17  18  24  25  37  39  43  46  48  52  53  55  60  65  69  78  79  80  83  84  85  86  93  94  95
Group 4: Users 21   23   27   31   35   36   54   58   61   64   70   75   76   81   92  100
Group 5: Users 26  32  99
Group 6: Users 91
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Fig. 6: SAUG results with 100 users and an angle threshold of 30 degrees for grouping

Furthermore, examples of the hybrid beamformed signal paths, the SAUG's output, the comparison between the transmitted signal versus received signal, and the terrestrial NLOS pathways vs HAPS pathways are detailed. The SAUG represents an important metric for grouping users within a specific cluster to optimize the distribution of power. Figure 6 highlights an example of grouping based on various spatial angles.

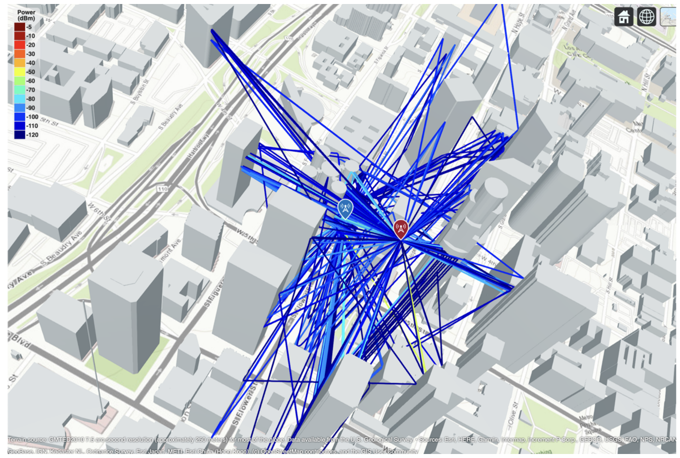

Fig. 7: Massive MIMO propagation paths with reflection for terrestrial drone (red) over Downtown LA (NLOS)

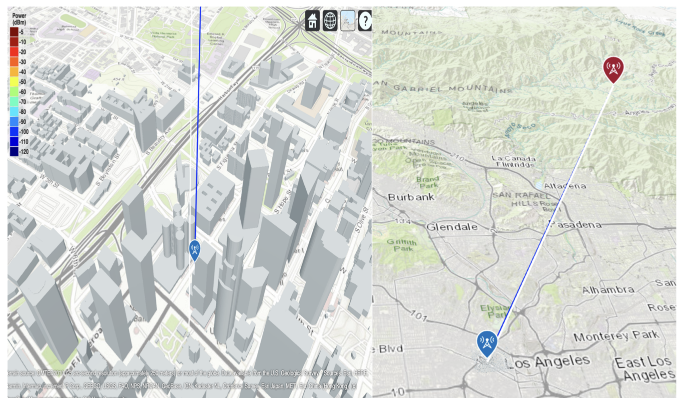


Fig. 8: Massive MIMO propagation paths with reflection for HAPS over Downtown LA (LOS)


Fig. 9: Actual massive MIMO radiation pattern for HAPS over Downtown LA (LOS)

In Figure 7, the intricate propagation paths are visually depicted, illustrating the complex trajectory resulting from ray-tracing based on reflections off the buildings or ground initially cast by the red transmitting antenna. This complexity arises from the disorderly nature of the NLOS urban environment, leading to a myriad of scattering paths. In contrast, Figure 8 illustrates the opposite effect, simple trajectories resulting from reflections that are engendered by the massive MIMO system onboard the HAPS.

Moreover, Figure 9 shows an example of what the massive

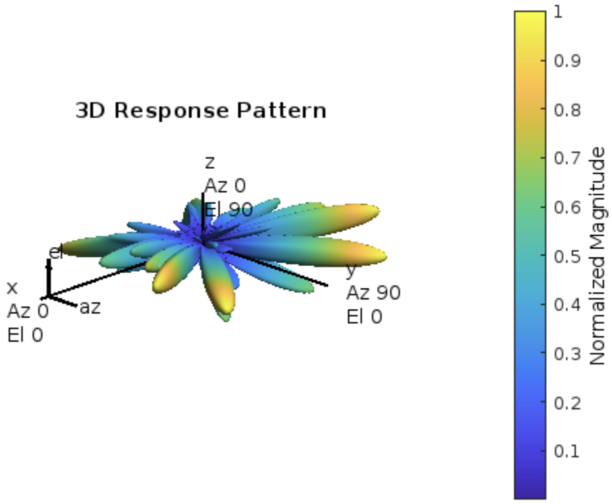


Fig. 10: Hybrid beamformed response pattern for a 16 x 16 MIMO for users in 5 different groups

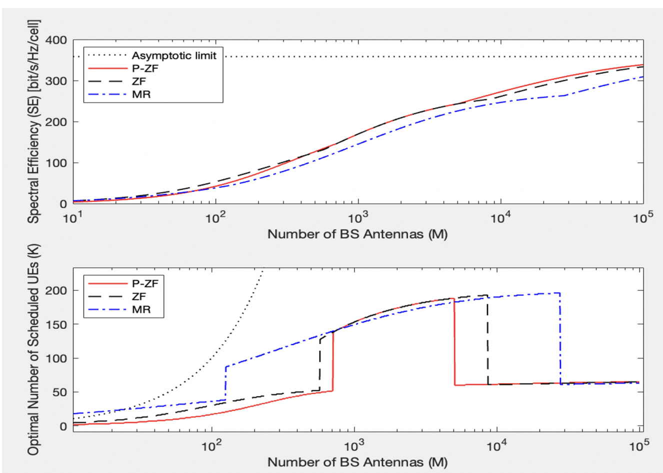


Fig. 11: Suitable number of UT given varying number of base station antennas [17]

MIMO radiation pattern would look like as it radiates over Downtown LA. Note that the grounded blue antenna indicates the receiving antenna.

Hybrid beamforming in massive MIMO systems specifically for HAPS presents an integration of analog and digital elements, yielding reduced power consumption and cost efficiency. The pattern shown in Figure 10 shows enhanced spectral efficiency through concurrent transmission of multiple data streams. This is particularly valuable in the context of millimeter-wave bands where propagation losses are significant. Figure 11 shows how the number of user terminals corresponds with the number of base station antennas. Notably, there's an optimal number of base station antennas for achieving higher number of user equipment and better proportional spectral efficiency. It is important to note that due to changes in frequency reuse algorithms in terms of fractional, cell-free, or cell, the most important parameter becomes the number of base station antennas rather than the frequency reuse number.

## IX. Conclusion

As seen from the results, the BER was shown to be superior slightly for a massive MIMO system incorporated by a HAPS, rather than a LEO.Furthermore, with MMSE precoding technique and a greater number of receiving antennas, the BER was less than that of ZF precoding with less receiving antennas. As a result, the performance for a massive MIMO on a HAPS is slightly more effective than that of a LEO. As the number of transmitting and receiving antennas grow, the signal strength and magnitude can dramatically increase due to having a bigger gain. It should be stated that the SAUG algorithm can be utilized for dividing users based on a small angular arc range of the beam. Additionally, the text's discussion on Rician fading and zero-forcing precoding emphasizes the importance of these techniques in mitigating signal degradation and interference. With the accumulation of training data, the adaptive alignment of MIMO capabilities with varying user mobility patterns and user density distributions will be pivotal in meeting the ever-increasing demands for optimal wireless communications. In essence, this innovative fusion of HAPS and massive MIMO technology holds the promise of revolutionizing wireless communication systems, catering to the evolving needs of our digital world, and showcasing the synergy of technology and infrastructure in propelling communication networks forward.

## X. Future Work

Future investigations should address other types of precoding methods for massive MIMO on LEO and on HAPS including matched filter and hybrid precoding techniques. Additionally, cases for non-geostationary HAPS should be considered as well. In this case, there would be a Doppler shift due to the mobility of a non-stationary drone or airplane-based HAPS as shown in Figure 12.

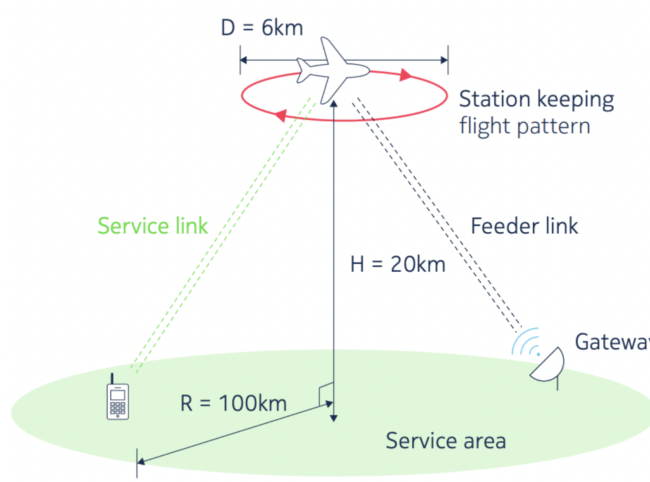


Fig. 12: Conventional deployment of airplane-fitted HAPS [16]

Environmental factors like wind should also be considered as they can lead to undesired platform motion, increased Doppler shifting, and antenna misalignment, which alone can decrease the effectiveness of beamforming drastically and diminish spatial diversity. Within the horizon of future developments, it becomes imperative to amass substantial reservoirs of training data for predictive purposes.

With the accumulation of this data, HAPS systems may proactively align their MIMO capabilities to contend with varying user mobility patterns and user density distributions across diverse environmental settings. This will lead to meeting user demands for optimal wireless communications within the service area.

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