Optimizing Resource Allocation in 5G MIMO Networks Using DUDe Techniques

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Abstract—**In the landscape of 5G networks, efficient resource allocation stands as a critical factor in meeting the diverse demands of applications and users. This paper delves into optimizing resource allocation within 5G Multiple Input Multiple Output (MIMO) networks by leveraging Downlink/Uplink Decoupling (DUDe) techniques. MIMO technology, enabling the simultaneous transmission of multiple data streams, holds promise for boosting spectral efficiency. However, accommodating the dynamic and diverse user requirements poses a significant challenge in resource allocation. By employing advanced DUDe techniques, this research aims to dynamically allocate resources in 5G MIMO networks, seeking to enhance throughput, minimize latency, and optimize user satisfaction. Through simulation-based analysis, this paper highlights the efficacy of the proposed approach in significantly improving network performance and resource utilization.**

Keywords—Downlink/Uplink Decoupling (DUDe), 5G Networks, Resource Allocation, Heterogeneous Networks, Multiple Input Multiple Output (MIMO)

I. INTRODUCTION

The advent of fifth generation (5G) communication networks signifies a transformative leap in connectivity, promising revolutionary advancements across industries and daily life. Among the pivotal challenges in maximizing the potential of 5G networks is the efficient allocation of resources, particularly within the domain of Multiple Input Multiple Output (MIMO) technology. MIMO's capability to facilitate the concurrent transmission of multiple data streams through multiple antennas presents an enticing avenue for augmenting spectral efficiency and accommodating the burgeoning demand for high data rates.

However, the intricate landscape of 5G networks, coupled with the ever evolving and heterogeneous user requirements, poses a formidable hurdle in optimizing resource allocation. Traditional methodologies often falter in dynamically adapting to these diverse demands, necessitating innovative approaches to bolster resource utilization while ensuring optimal network performance and user experience.

This paper embarks on a distinctive trajectory by promoting the application of Downlink/Uplink Decoupling (DUDe) techniques for resource allocation within 5G MIMO networks. In traditional cellular systems, the assignment of User Equipment (UE) to the Base Stations (BSs) is based on the DL Signal to Noise Ratio (SNR) of the UE (and both Downlink (DL)-Uplink (UL) are connected to the same BS), while in the case of DUDe the assignment of UEs UL and DL to the Base Station (BS) is based both on the UL SNR and DL SNR of the UE (and UL and DL can be connected in difference BSs). DUDe offers enhancing resource allocation efficiency and network resource utilization. For additional information refer to [1].

The unique proposition lies in the decoupling of downlink and uplink resources, aiming to dynamically allocate resources to maximize throughput, minimize latency, and elevate user satisfaction levels. Ultimately, this research contributes to the ongoing discourse in the domain of 5G network enhancement by shedding light on the transformative capabilities of MIMO technology in refining resource allocation strategies using DeepMIMO [2], a data generator for mmWave/massive MIMO channels, resulting in an upgraded simulation tool that offers more accurate and realistic representations of 5G network challenges. By providing empirical insights into the effectiveness of DeepMIMO-enhanced resource allocation, this study aspires to catalyze the development of more efficient and adaptive 5G network infrastructures [3], [4], [5], [6].

Unlike previous works that primarily focus on traditional resource allocation algorithms, our study leverages DUDe techniques to dynamically adapt to changing network conditions and user demands. This innovation allows for more flexible and adaptive resource allocation strategies, enabling the network to efficiently utilize available resources while meeting the diverse requirements of different users. To the best of our knowledge, the only similar research is presented in [7], with the difference being that our research focuses on bandwidth allocation among BS, whereas the work in [7] aims at optimizing the spectrum efficiency of the BS.

Moreover, the implementation of DUDe not only facilitates the seamless integration of new users into the network, but also ensures uninterrupted service. The smoother distribution, not only guarantees available capacity for Base Stations (BS), but also prevents them from reaching their capacity limits, even when dealing with a substantial number of users. This approach not only enhances network capacity, but also contributes to a more robust and interference-resistant communication environment for users. The existing literature on enhancing resource allocation in Heterogeneous Network (HetNets) MIMO 5G networks encompasses a range of innovative approaches. The work in paper [8] discusses the integration of Py5cheSim, a Python-based 5G network simulator with DeepMIMO. This tool is significant for its advanced approach to network simulation and resource allocation.

The authors of [9] examine the critical aspect of resource allocation, especially in the context of Massive-MIMO technology, which allows for the simultaneous scheduling of multiple users on the same frequency resource. Paper [9] highlights the importance of user grouping strategies to minimize interference and points out the limitations of such strategies within systems using a block diagonal precoder. Paper [10], focuses on optimizing Resource Allocation (RA) and Transmit Antenna Selection (TAS) in millimeter-wave massive MIMO communications. The paper introduces an approach that uses the Attention-Based Capsule Auto-Encoder (ACAE) architecture and the Battle Royale Optimization (BRO) technique to improve transmission reliability and channel capacity while minimizing hardware costs. Finally, it emphasizes on efficiency enhancements in 5G communications through advanced optimization techniques.

Paper [11], delves into Cell-free Massive MIMO, a promising architecture for 5G networks that addresses resource allocation challenges in downlink networks. The paper presents an iterative algorithm that efficiently handles the optimization problem posed by coupled interference among User Equipment (UE), demonstrating the effectiveness of the algorithm in practical scenarios. Finally, paper [12] focuses on the need for high energy efficiency in future wireless networks to achieve net-zero greenhouse gas emissions. The paper proposes a power consumption model that considers the effects of carrier aggregation and spatial layering on 5G network power consumption, advocating for the optimization of active antennas and physical resource blocks to enhance energy efficiency.

The rest of our paper is organized as follows: Section II, introduces the mathematical model utilized in our simulation environment. Section III, delves into the algorithm analysis that forms the basis for constructing our experiment scenarios. Section IV outlines the simulation setup and methodology employed to assess the performance of DUDe in our MIMO 5G HetNets. Section V, presents the simulation results and provides a comprehensive analysis of the findings. Lastly, Section VI presents our conclusions and offers insights into potential avenues for future research.

II. MATHEMATICAL MODEL

In this section, we provide a comprehensive overview of the mathematical model that we used in our experiments. Initially, to ascertain the minimum distance between UEs and various BS antennas, we employ the mathematical model outlined in TR 38.901 Section 7.4.1 [13]. We must note that a thorough examination of the factors outlined below is not within the purview of this paper.

$$PL_{\text{RMa-LOS}} = \begin{cases} PL_1 & 10m \le d_{\text{2D}} \le d_{\text{BP}} \\ PL_2 & d_{\text{BP}} \le d_{\text{2D}} \le 10\text{km} \end{cases} \quad (1)$$

$$\begin{aligned} PL_1 &= 20\, log_{10}(40\pi d_{\text{3D}} f_c/3) + min(0.03h^{1.72}, 10)\, log_{10}(d_{\text{3D}}) \\ &\quad - min(0.044h^{1.72}, 14.77) + 0.002\, log_{10}(h) d_{\text{3D}} \end{aligned} \quad (2)$$

$$PL_2 = PL_1(d_{\text{BP}}) + 40\, log_{10}(d_{\text{3D}}/d_{\text{BP}}) \quad (3)$$

Once the pathloss is determined through the 5G Matlab model, which includes the aforementioned functions and equations, we utilize the result of the nrpathloss function to calculate the SNR to determine the closest antenna for establishing connections. The SNR mathematical expression involves measuring both signal power and noise power at the same or equivalent points in the system and within the same bandwidth. The mathematical expression for SNR is as follows:

$$\text{SNR} = \text{Psignal}/\text{Pnoise} \quad (4)$$

For scenarios involving bandwidth allocation, we compute the maximum bandwidth limit for UEs for each antenna using the Shannon-Hartley theorem [14]. This theorem, a cornerstone in information theory named after Claude Shannon and Ralph Hartley, establishes the maximum error-free information transmission rate over a communication channel with a given bandwidth, considering noise presence. It aids in optimizing communication system design by finding the balance between information transfer rate and error minimization.

$$C = Blog_2(1 + S/N) \quad (5)$$

The channel capacity (C), measured in bits per second, represents the maximum achievable net bit rate without error-correction codes. Bandwidth (B) denotes the passband bandwidth for a bandpass signal. The SNR, expressed as a linear power ratio, compares communication signal power to noise and interference power at the receiver.

III. ALGORITHM ANALYSIS

This section presents the analysis of the theoretical algorithm which we have evaluated through simulations supported by the DeepMIMO toolkit [2]. The algorithm starts by getting important information from the DeepMIMO dataset, including details about BS, UEs, and the communication channel. It then considers system parameters and does essential calculations, like figuring out Noise Power based on the system's bandwidth. Initial variables, such as Effective Isotropic Radiated Power (EIRP), user counters, and antenna parameters, are set up.

Moving on, the algorithm calculates the distances between each BS and its UEs. At the same time, it calculates the path loss for each BS-UE pair, giving insights into signal strength. Next, the algorithm calculates SNR for both uplink and downlink, taking into account factors like transmit power, antenna gains, path loss, and noise power. These SNR values indicate the quality of the communication channels. UEs are then randomly assigned services, like Browsing/Email or HDTV, which are matched with corresponding downstream and upstream values, shaping each UE's communication requirements. The analytical specifics regarding both the downstream and upstream services of the UEs are outlined in the next section.

A dynamic structure called 'dynamic_pathloss_BS_ue' is created to hold UE-specific information, including SNR, assigned services, and bandwidth requirements. UEs are sorted based on downlink SNR values in descending order for each BS. This sorting is crucial for later steps where choosing the best BS becomes important. Capacity-related variables for each BS are set up, creating the stage for dynamic capacity allocation. The overall system capacity, labeled as 'BScapacity,' is established as a reference point for understanding available resources. The algorithm then goes through UEs based on their sorted SNR values. For each UE, it finds the BS with the highest combined cost, considering SNR and available capacity. The algorithm checks if the selected BS has enough capacity to meet the UE's downstream requirements. If it does, capacity is allocated, and the information is updated. The allocated information is organized into an array called 'success_throughput.' This array provides crucial details about UEs, BS, and the data rates achieved during communication. Briefly, the algorithm dynamically allocates communication resources, considering UE needs and channel conditions. The final 'success_throughput' array encapsulates valuable insights into this allocation process.

When it comes to complexity, the algorithm's efficiency is mainly influenced by sorting and allocation steps, both having a complexity of O(N^2). The space complexity is affected by the data structures used to store path loss information, allocated resources, and the final results.

Algorithm 1 Algorithm for resource allocation in our 5G MIMO network.

 # Step 1: Initialization
Load DeepMIMO dataset
Read parameters from 'parameters.m'
Calculate Noise Power (Pn)
Initialize variables (EIRP, UE counters, etc.)
 # Step 2: Distance and Path Loss Calculation
For each BS:
  For each UE:
    Calculate Euclidean distance
    Calculate path loss
 # Step 3: SNR Calculation
For each BS:
  For each UE:
    Calculate downlink SNR
    Calculate uplink SNR
 # Step 4: User Services Assignment
For each UE:
  Assign random services (e.g., Browsing/Email, HDTV, etc.)
  Match services with downstream and upstream values
 # Step 5: Dynamic Path Loss Structure Initialization
Create dynamic structure 'dynamic_pathloss_BS_ue'
 # Step 6: Sorting Users Based on SNR
Sort UEs based on downlink SNR in descending order for each BS
 # Step 7: Capacity Initialization
Initialize capacity-related variables for each BS
Define overall system capacity ('BScapacity')
 # Step 8: Dynamic Capacity Allocation
For each UE:
  Find BS with highest combined cost
  Check if selected BS has available capacity for UE's downstream requirement
  If yes, allocate capacity and update information
 # Step 9: Result Structuring
Structure allocated information into 'success_throughput' array
Calculate achieved data rates for each UE
 # Step 10: Algorithm Output
Output 'success_throughput' array
 # Step 11: Complexity Analysis
Time complexity: O(N^2) for sorting and allocation
Space complexity: Influenced by data structures (path loss, allocated information, results)

IV. Simulations Environment

In this section, we aim to provide a comprehensive insight into the intricacies of our simulated network structure and its associated parameters. It is essential to highlight that both the topology and the dataset guiding our simulation setup were sourced from the DeepMIMO platform. This platform serves as a valuable resource, offering the necessary infrastructure to shape and execute our experiments effectively. More specifically we have a HetNet 5G MIMO network setup as seen in Fig. 1. This setup is about an urban setting where the main street, stretching horizontally, spans 600 meters in length and 40 meters in width and a vertical counterpart spanning 440 meters in length and 40 meters in width. Similar to the main street, buildings line both sides, contributing to the city's architectural tapestry. Along the main street, uniformity prevails as all buildings share bases with dimensions of 30 meters by 60 meters. On the other hand, the second street exhibits a distinct architectural style, with buildings standing on bases measuring 60 meters by 60 meters.

Additionally, we have installed a total of 18 BSs named BS1 through BS18, all standing at a height of 6 meters. Now, if we stroll down the main street, we will encounter 12 of these stations—BS1 to BS12—with 6 stationed on each side. Regarding the spacing arrangement, there is a 52-meter gap between the BS on one side of the street and those on the opposite side. Breaking it down further, there is a 100-meter separation between clusters—BS1, BS3, and BS5; BS2, BS4, and BS6; BS7, BS9, and BS11; BS8, BS10, and BS12.Adding a bit more flair, there is a tighter 62-meter spacing between BS6 and BS8, as well as between BSN5 and BS7.

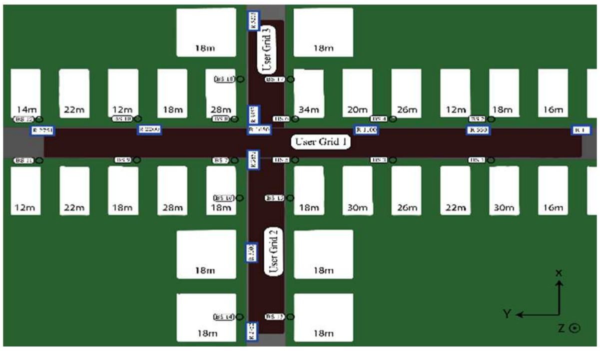

Fig. 1. General topology of simulated network.

Moreover, in the second street, BS13 to BS18 are holding their ground. Each side of the street hosts 3 BS, and there is a roomy 150-meter gap between BS13, BS15, and BS17, as well as between BS14, BS16, and BS18. Delving deeper into the specifics, we find a 52-meter separation between adjacent stations—BS13 and BS14, BS15 and BS16, and BS17 and BS18. So, with these dimensions and placements, the network is all set to weave its connectivity magic throughout the urban landscape.

Additionally, we have three distinct User Grids (UG) – UG1, UG2, and UG3 in which up to 1,184,923 UEs can be accommodated. Adding a touch of strategic placement, the first UE in each grid claims the distinction of having the lowest (x, y) coordinates. Uniformity reigns in the height department, with all UE grids maintaining a consistent 2-meter elevation.

UG1 takes center stage, stretching horizontally along the main street for 550 meters with a width of 35 meters. Its lineup kicks off 15 meters after the street's beginning and gracefully concludes just before the endpoint. Across 2751 rows, each housing 181 UEs with identical y-coordinates, UG1 fosters a sense of community with a 20 cm spacing between UEs, boasting a total of 497,931 UEs. UG2, on the other hand, seizes attention on the southern side of the cross street. Spanning rows 2752 to 3852, a total of 1101 rows host 181 UEs each, maintaining a 20 cm gap between neighbors. UG2's vibrant community consists of 199,281 UEs. In UG3 which conclude rows 3853 to 5203, serve as the prime real estate, accommodating 1351 rows with 361 UEs per row. Slightly cozier with a 10 cm spacing between UEs, UG3 is home to 487,711 UEs, fostering a closer network camaraderie.

Eventually for our experiments, we have designated specific areas for our implementation. Fig. 2 illustrates the chosen locations: User Grid 3 will utilize BS17 and from User Grid 1 will rely on BS4, BS3, BS5 and BS6, BS7. The BS transmit power is configured at 45 dBm, accompanied by a gain set at 21 dBi. To explore various user scenarios, we will conduct three setups involving 180, 360, and 724 UEs, all while maintaining a consistent UE power of 20 dBm. Also, you can find a summary of these network parameters in Table I. Finally, in bandwidth allocation scenarios, we create a random number of UE and assign each UE to one of the services outlined in Table II, where the downstream and upstream demands per service are presented.

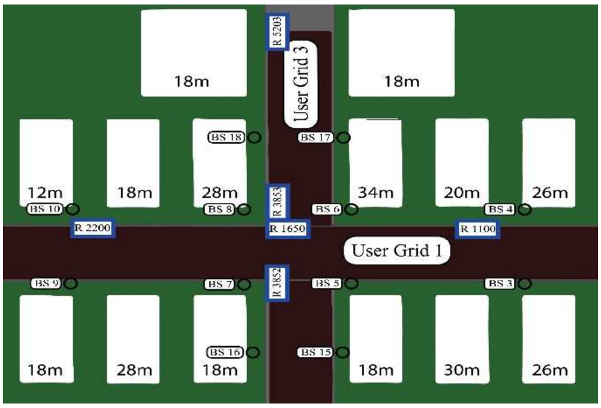

Fig. 2. Topology of first simulations.

Also, we run another experiment where Fig. 3 illustrates the chosen locations: User Grid 3 will be connected to BS17, while User Grid 1 will utilize BS4, BS3, BS5, BS6, BS7, BS8, and BS15. This adjustment in network topology aims to investigate whether it influences the underlying assumptions we have made.

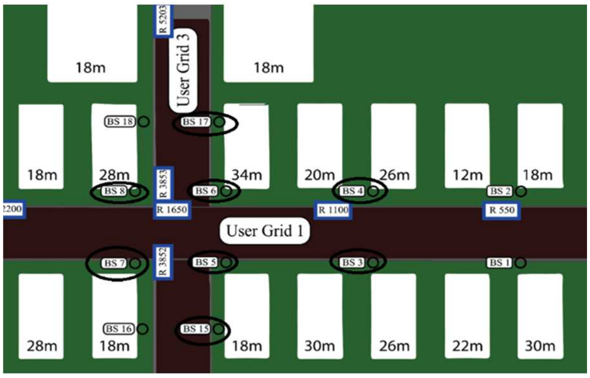

Fig. 3. Topology of second simulations.

To ensure equitable resource distribution across antennas while achieving optimal performance, we employ DUDe technology. Notably, our approach diverges from previous research by incorporating a MIMO system, where each BS is equipped with 2000 antennas. To highlight this point, every mentioned antenna corresponds to a UE. This setup allows UEs to connect to multiple antennas, enhancing system performance. Our objective is to demonstrate the efficacy of DUDe application in such a system, where UEs have multiple connection options, compared to alternative resource allocation technologies in telecommunications networks. Note also, that the operating frequency of the network in which simulations were implemented is at 140 GHz, the Number of 5G NR resource blocks is 60 and 5G Subcarrier spacing in kHz is 120.

TABLE I. SIMULATION PARAMETERS

Parameter	Value
Transmit power(dbm)	45 dbm
BS height (m)	6 m
BS/UE gain (dbi)	21 dbi, 0 dbi
Bandwidth (MHz)	400 Mhz
Number Of UEs	180,360,724, 905
Power Noise	Pnoise= -74+10log(Bandwidth(hz))

TABLE II. TYPE OF SERVICES

Services	Downstream	Upsteam
Browsing/Email	5 Mbps	2 Mbps
HDTV	16 Mbps	0.5 Mbps
Video Streaming	25 Mbps	1 Mbps
Podcasts	2 Mbps	0.5 Mbps
VoIP	1 Mbps	1 Mbps

V. SIMULATION RESULTS

In this section, we delve into our simulations and analyze the conclusions drawn from them, aiming to validate our initial research on the subject. To conduct these experiments, we have generated three separate datasheets, each corresponding to scenarios with 362, 543, 724 and 905 UEs. Also, in the scenario involving 905 UEs, we implement the alternative topology described earlier. These UEs are placed within the network topology we previously analyzed, leveraging the nrpathloss function in Matlab to ensure random yet evenly distributed placements. Specifically, we maintain a one-meter distance between each UE to prevent overlapping.

In calculating the SNR, we consider several factors. These include the transmission power of the antenna and the UE, which is held constant at 20 dB for our experiments. Additionally, we account for antenna gain, which is 21dbi and 0 dbi for UE. The distance between the antenna and the UE is also factored in. Finally, we incorporate noise into the calculation. By considering these elements, we ensure an accurate assessment of SNR, a crucial metric in determining the quality of wireless communication links.

Our antennas possess a fixed bandwidth capacity of 400 MHz. In all scenarios, UEs are assigned to antennas using a specific procedure. Initially, we calculate the SNR based on each UE's distance from the antennas. Subsequently, we assess whether the antenna has adequate resources (bandwidth capacity) to accommodate the UE's service. If so, we connect the UE to the optimal antenna; otherwise, we connect them to the nearest antenna based on SNR value. This method ensures every UE receives satisfactory service.

Through graph analysis, we elucidated the nuanced performance characteristics of DUDe and DUCo technologies in a MIMO 5G network setting. By discerning trends and patterns from the graphical representations, we gained insights into the efficacy of these technologies in managing network resources and delivering optimal user experiences. These findings pave the way for informed decision-making in network design, deployment, and optimization in the burgeoning field of 5G communications. Also, for a better understanding of our plots, it is worth mentioning that these are bar plots depicting the remaining bandwidth per BS for both DUDe and DUCo technologies. Each line in the graph represents a specific base station, while the height of the bar indicates the remaining bandwidth in Hertz (Hz).

By visually comparing the blue (DUDe) and orange (DUCo) bars, we can see how these technologies affect bandwidth availability at different base stations.

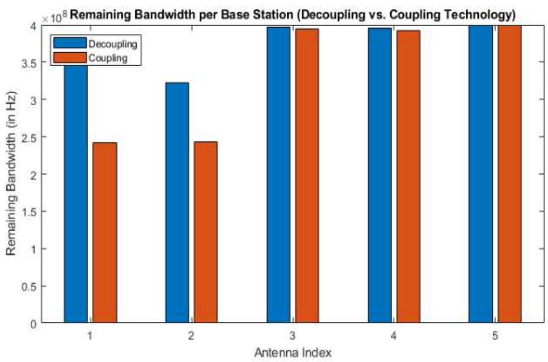

Fig. 4. Bandwidth Consumption for 362 UEs.

Firstly, in case of 362 UE the diagram above in Fig. 4, consistently reveals that DUDe technology consistently uses less bandwidth per antenna compared to coupling technology in this specific 5G MIMO setup. This implies that decoupling technology is generally better at making the most out of available bandwidth in this scenario. The fact that this efficiency pattern is consistent across all antennas suggests that it is not just a random occurrence but a systematic advantage of decoupling technology. These findings could be leveraged to support the argument that DUDe is the best option for effectively managing bandwidth in 5G networks.

Moving to Fig. 5 (543 UEs), while decoupled technology still generally maintains a lead in remaining bandwidth, the margin between decoupling and coupling is less pronounced compared to the scenario with more UEs. This suggests that as the number of UEs decreases, the performance gap between decoupled and coupled technology tends to narrow.

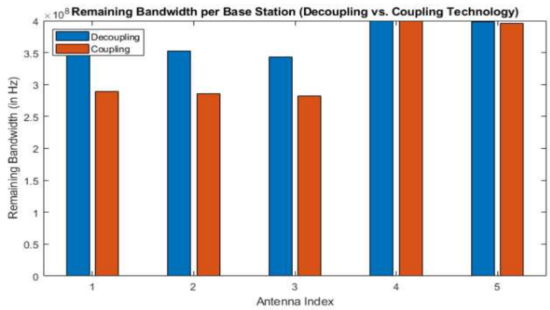

Fig. 5. Bandwidth Consumption for 543 UEs.

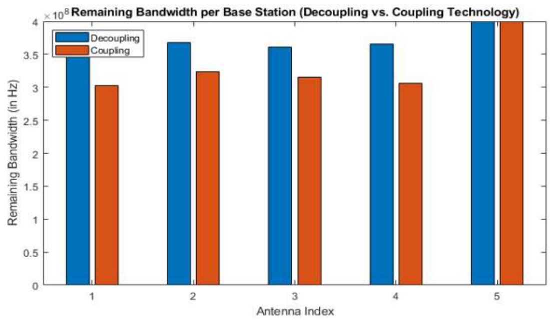

Fig. 6. Bandwidth Consumption for 724 UEs.

In Fig. 6 (724 UEs), the focus shifts to mean bandwidth consumption rather than remaining bandwidth. Here, decoupled technology continues to demonstrate lower average bandwidth consumption compared to coupled technology. Remarkably, even with fewer UEs, the disparity between decoupling and coupling technologies remains noticeable, indicating that decoupling technology may maintain its bandwidth efficiency advantage.

Also, by examining Fig. 7, we discovered that altering the network topology does not impact our original hypothesis. DUDe technology consistently demonstrates superior allocation efficiency among BSs compared to DUCo. This results in improved service for both existing and new BSs, affirming DUDe's effectiveness in optimizing network performance.

Across all scenarios, DUDe technology consistently outperforms DUCo technology in terms of bandwidth efficiency. This is evident from either having more remaining bandwidth or less mean bandwidth consumption in all the charts. The difference in performance between decoupling and coupling technology appears to be influenced by the number of UEs. With a higher UE count (724 vs. 543 vs. 362), the advantage of decoupling technology becomes more pronounced. Despite the overall trend favoring DUDe technology, the performance across BS indices is not uniform. This suggests that certain antennas may inherently perform better or worse, regardless of the DUDe or DUCo technology employed.

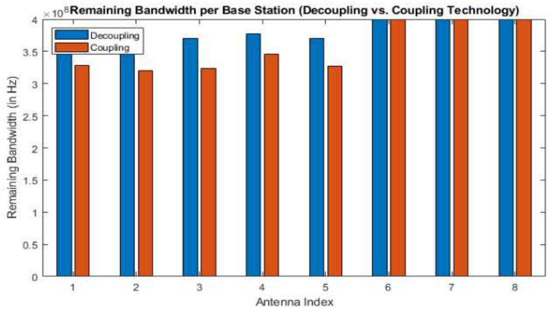

Fig. 7. Bandwidth Consumption for 905 UEs.

VI. Conclusion and Future Work

Our experiments demonstrate the efficacy of DUDe in managing the massive data demands in MIMO systems while ensuring efficient utilization of the available spectrum. The comparative analysis of decoupling versus coupling technology across various antenna indices with a varying number of UEs has revealed that decoupling consistently provides superior bandwidth efficiency. This is particularly significant in the context of 724, 543, and 362 UEs scenarios where the remaining bandwidth and mean bandwidth consumption per antenna have been substantially improved with decoupling. These findings underscore the potential of DUDe to enhance the capacity and reliability of next-generation wireless networks.

Moving forward, several avenues appear promising for extending this research. The scalability of DUDe techniques warrants further exploration, particularly in ultra-dense network environments where UE equipment numbers can substantially exceed the scales considered in this study. Additionally, integrating machine learning algorithms to predict and adapt to dynamic network demands in real-time could further optimize resource allocation. Further investigation into the interplay between different antenna technologies and DUDe techniques could yield additional insights, potentially guiding the development of more sophisticated antenna designs tailored to this approach. Lastly, field trials in live network environments would be invaluable in validating the performance of DUDe under practical operating conditions and diverse user behavior patterns. Also, we aim to explore resource allocation optimization in 5G MIMO DUDe heterogeneous networks using the Hungarian and minimum cost flow algorithms which we have already investigated in 5G MIMO (non- DUDe) Networks [15], [16].

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