Performance Evaluation of Downlink – Uplink Decoupling in 5G Multiple Input Multiple Output Networks

Tsachrelias Konstantinos[1], Chrysostomos-Athanasios Katsigiannis[1], Vasileios Kokkinos[1], Apostolos Gkamas[2], Christos Bouras[1], Philippos Pouyioutas[3]
[1]Computer Engineering and Informatics Department, University of Patras, Patras, Greece
[2]Department of Chemistry, University of Ioannina, Ioannina, Greece
[3]Computer Science Department, University of Nicosia, Nicosia, Cyprus

bouras@upatras.gr

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 dynamically allocates resources in 5G MIMO Heterogeneous Networks (HetNets), seeking to enhance throughput, minimize latency, and optimize user satisfaction. The paper includes scenarios involving varying User Equipment (UE) densities and mobility to evaluate system performance under different load conditions. Through simulation-based analysis, this paper highlights the efficacy of the proposed approach in significantly improving network performance, energy efficiency, and resource utilization.

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

1 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 Downlink (DL) Signal to Noise Ratio (SNR) of the UE and both DL-Uplink (UL) are connected to the same BS, a method known as Downlink/Uplink Coupling (DUCo), while in the case of DUDe the assignment of UEs UL and DL to the 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 enhanced resource allocation efficiency and network resource utilization. Additionally, DUDe lets a handset send its uplink traffic to the nearest small cell while still drawing downlink data from the macro layer, expanding the uplink link budget without extra user-side power. Field trials report uplink-rate gains above 50 % in dense 5G layouts, and the benefit grows when massive-MIMO receivers cancel intra-cell interference. In a smart classroom, that head-room lets every learner stream multi-view video from head-mounted cameras so instructors can respond in real time. During outdoor fieldwork, the same mechanism keeps sensor uploads steady while the device downloads augmented-reality overlays. Because DUDe re-uses the phone's existing 5G massive-MIMO antennas, campuses and micro-campuses can roll it out step by step and still give learners balanced two-way media even where budgets are tight. For additional information refer to [1], [2], [3].

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 [4], 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 [5], [6], [7], [8].

While the separation of DL and UL improves load balancing and link quality, it raises several implementation challenges. Channel-state information must be shared across two serving cells, adding fronthaul signalling and latency; uplink channel estimates collected at a small cell are no longer directly usable for the downlink handled by a macro cell, so extra sounding or coordinated pilots are needed; and tight time alignment is required to keep hybrid-ARQ and control signalling coherent across tiers. These practical concerns set DUDe apart from DUCo and frame the design choices analyzed in this work.

In this research, mobility scenarios are conducted to examine the network's performance in environments where the UEs is in motion. By simulating different mobility conditions, the network's ability to adapt to the changing positions of UEs while maintaining efficiency and performance is evaluated. Along with mobility, high-density scenarios are also considered, allowing for a comprehensive assessment of DUDe techniques. This combination of mobility and density scenarios provides valuable insights into DUDe's adaptability and effectiveness in real-world settings, offering a thorough evaluation of its potential to optimize resource allocation and enhance network performance in diverse 5G environments. These scenarios not only validate the proposed algorithm but also deepen the understanding of how DUDe improves resource utilization under varying conditions.

Finally, this research explores the impact of varying power levels on energy efficiency and power consumption within 5G MIMO networks. By examining the relationship between transmitting power, energy efficiency, and the overall power requirements of the network, further insights are gained into the balance between supporting higher data rates and maintaining efficient power usage. This aspect of the study is crucial in understanding how increased user demand, paired with elevated transmission power, influences both the performance and sustainability of the network. The findings from this analysis are integral in guiding future designs of energy-efficient 5G networks that can adapt to growing user densities while minimizing power consumption.

The rest of the paper is organized as follows: Section 2 presents various research studies that utilize DUDe and MIMO technologies for their respective applications. Section 3 introduces the mathematical model utilized in the simulation environment. Section 4 delves into the algorithm analysis that forms the basis for constructing experiment scenarios. Section 5 outlines the simulation setup and methodology employed to assess the performance of DUDe in the MIMO 5G Heterogeneous Network (HetNet). Section 6 presents the simulation results and provides a comprehensive analysis of the findings. Section 7 presents the conclusions and lastly, section VIII offers insights into potential avenues for future research.

2 Related Work

Looking at the literature, important research highlights the benefits of applying DUDe in 5G MIMO networks. Studies show that DUDe enhances network performance by allowing separate handling of DL and UL connections, improving flexibility and resource efficiency.

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 BSs, 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 HetNets MIMO 5G networks encompasses a range of innovative approaches. Authors in [9] extend DUDe association to a two-tier wireless-powered HetNet that pairs massive MIMO macrocells with full duplex small cells. They introduce mean-maximum-power and maximum-power harvesting rules, then use stochastic geometry to obtain closed form expressions for harvested energy and UL/DL coverage. The analysis reveals an optimal small-cell density and shows energy-efficiency gains of roughly 1.4× over conventional coupled association and networks without wireless power transfer, while also mapping how macrocell power, antenna count, and self-interference affect these gains. The work provides a tractable baseline for designing energy-aware DUDe deployments in full-duplex HetNets.

The authors of [10] explored DUDe as a bandwidth-optimization tool. Allowing each user to attach to separate base stations for the two links lets the scheduler adjust spectrum to real-time traffic and channel conditions. Simulations showed that DUDe eases macro-cell congestion, evens out user distribution across antennas, and boosts end-to-end throughput over traditional coupled allocation. The analysis also pinpoints system factors that shape these gains and suggests extending the approach to multi-access scenarios and joint optimization with complementary techniques. Paper [11],study measures the energy cost of DUDe in 5G by accounting for each base station's power draw and the signalling overhead between cells and users. Simulations across a range of user densities, cell layouts, and traffic profiles show that DUDe reduces total network consumption compared with conventional coupled access, mainly by reallocating uplink traffic to less-loaded sites. The authors also map how configuration choices—such as base-station density and traffic mix—shape these savings, offering practical guidelines for energy-aware network planning.

Paper [12] 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 UE, demonstrating the effectiveness of the algorithm in practical scenarios. Paper [13] 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.

Paper [14] constitutes a notable contribution to resource allocation in 5G-NR systems is presented in the work on downlink resource allocation for 5G-NR massive MIMO systems. This study addresses the challenges posed by beamforming and spatial multiplexing in 5G-NR, which require optimized resource allocation across time, frequency, and space to fully realize the capacity gains from massive MIMO. Unlike traditional 4G-LTE algorithms, which do not account for the dual-channel nature of 5G-NR, this work proposes a joint allocation scheme for both control and shared channels. The authors formulate the problem as an integer linear program and propose sub-optimal and approximation algorithms for practical implementation. Simulation results demonstrate that the proposed algorithms significantly outperform baseline approaches in terms of sum-throughput and fairness, offering a promising solution for enhancing resource allocation in 5G-NR networks.

Another significant contribution to resource allocation in 5G heterogeneous networks is presented in research [15], which focuses on the joint optimization of Resource Allocation (RA), User Association (UA), and Power Control (PC) for LTE-A networks. This study addresses the complexities of optimizing multiple parameters simultaneously, such as energy efficiency, spectrum efficiency, and queue length in MIMO-based systems. By utilizing a mixed-integer programming model and a Drift-Plus-Penalty (DPP) approach for Lyapunov optimization, the authors propose a solution for downlink transmission resource allocation that accounts for both macro and small cells. The work introduces a reduced problem approach through linear relaxation, making it more computationally efficient even for NP-hard problems. Numerical results demonstrate that the proposed framework effectively balances energy and spectrum efficiency while outperforming traditional greedy algorithms in terms of performance metrics.

In recent research [16], a DUDe access scheme for Unmanned Aerial Vehicle (UAV) communication systems was proposed, focusing on minimizing interference by separating the control and data links of UAVs and decoupling the uplinks and downlinks of ground users onto different base stations and frequencies. To address power constraints, two reinforcement learning-based power allocation schemes, Q-Learning (QL) and Deep Q-Learning (DQL), were introduced to optimize communication energy efficiency. Compared with traditional fractional power control schemes, the DUDe approach with QL and DQL demonstrated significantly higher energy efficiency and sum rates, with improvements of 80%–100% in the Ultra High Frequency (UHF) band and 160%–170% in the mmWave band. The study concluded that while QL and DQL can achieve near-optimal energy efficiency, DQL outperforms QL due to its ability to handle a larger state space, highlighting the effectiveness of reinforcement learning in optimizing resource allocation within the DUDe framework for 5G networks.

Unlike previous works that primarily focus on traditional resource allocation algorithms, this 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. The only similar research, that was found, is presented in [17], with the difference being that this research focuses on bandwidth allocation among BS, whereas the work [17] aims at optimizing the spectrum efficiency of the BS.

3 Mathematical Model

This section provides an overview of the mathematical model used in the experiments. Initially, to determine the minimum distance between UEs and various BS antennas, the model outlined in TR 38.901 Section 7.4.1 [18] is employed. The following equations 1 to 3 calculate the pathloss for each UE; however, a detailed analysis of these equations lies beyond the scope of this paper.

$$PL_{\mathrm{RMa-LOS}} = \begin{cases} PL_1 & 10m \leq d_{\mathrm{2D}} \leq d_{\mathrm{BP}} \\ PL_2 & d_{\mathrm{BP}} \leq d_{\mathrm{2D}} \leq 10\mathrm{km} \end{cases} \tag{1}$$

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

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

Once the pathloss is determined through the 5G Matlab model, which includes the aforementioned functions and equations, the SNR is calculated 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, the maximum bandwidth limit for UEs for each antenna, is computed, using the Shannon-Hartley theorem **Σφάλμα! Το αρχείο προέλευσης της αναφοράς δεν βρέθηκε.**. This theorem 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 power at the receiver.

4 Algorithm Analysis

This section presents the analysis of the theoretical algorithm which has been evaluated through simulations supported by the DeepMIMO toolkit [2].

Algorithm I: A Dynamic Game-Theoretic Algorithm for Multi BSs n UE Allocation

1. **Step 1: Initialization & Parameter Configuration:**
2. Load the DeepMIMO dataset, read the parameters in parameters.m, compute the noise power Pn, and set up EIRP along with all UE and BS counters..
3. **Step 2: Distance & Path-Loss Calculation:**
4. For every base station and each user, calculate the Euclidean distance and then derive the corresponding path loss..
5. **Step 3 SNR Calculation:**
6. Using the path loss, compute both the downlink and uplink SNRs for every BS–UE pair. UL and DL link qualities are kept separate.

7. **Step 4 Primary BS Selection:**
8. For every UE, the algorithm separately determines:
the base station that maximises received signal strength on the downlink, and
the base station that maximises received signal quality on the uplink.
The UE is then associated with the first station for downlink transmissions and, if different, with the second station for uplink transmissions. When the same base station is optimal for both directions, the procedure coincides with the conventional coupled scheme.
9. **Step 5 User-Service Assignment:**
10. For each UE, randomly pick a service (e.g., browsing, HDTV, VR) and map its down- and upstream rate demands.
Step 6 Dynamic Path-Loss Structure:
11. Create an on-the-fly data structure called dynamic_pathloss_BS_ue to store updated path-loss values.
12. **Step 7: SNR-Based UE Sorting**
13. Within every BS, sort its associated UEs by descending downlink SNR.
14. **Step 9: Capacity Initialization:**
15. Create an on-the-fly data structure called dynamic_pathloss_BS_ue to store updated path-loss values.
16. **Step 10: Dynamic Capacity Allocation:**
17. Iterate through the sorted UEs, choose the BS offering the lowest combined cost, and, if enough capacity remains, allocate the UE's downstream demand and update all records.
18. **Step 11: Result Structuring:**
19. Aggregate the successful allocations in success_throughput and compute each UE's achieved data rates.
20. **Step 12: Algorithm Output:**
21. Return the populated success_throughput array.
22. **Step 13: Complexity Analysis:**
23. The overall time complexity is O(N2) for sorting and allocation, and the space cost comes mainly from the path-loss, allocation, and result structures.
24. **Step 14: High-Mobility Scenarios:**
25. Group UEs by speed (pedestrian, vehicular, high-speed), simulate handovers, packet loss, and latency, compute the averages per group, and plot handover frequency, packet loss, and latency against speed.
26. **Step 15: Energy Efficiency & Power Consumption:**
27. Sweep predefined power levels, calculate each UE's power draw, derive its bits-per-watt efficiency from the downlink SNR, average the results, and plot energy efficiency and power consumption versus power level.

The procedure begins by loading DeepMIMO channel data and reading all system parameters. It computes the thermal-noise power from the bandwidth, sets the effective isotropic radiated power, and initializes counters for every BS and UE. Next, it calculates the Euclidean distance and path loss for every BS-UE pair, then converts these losses into separate downlink and uplink SNR matrices. Each UE is randomly assigned a service class e-mail, web browsing, HDTV, or similar and the corresponding rate requirements for both directions are added to a dynamic table that also stores its path loss and SNR values.

In the primary base-station selection phase, each user evaluates the channel to every cell, picks the one that delivers the strongest downlink signal for receiving data, and independently picks the one that offers the highest uplink SNR for sending data; the user then downloads through the first cell and, if the two selections differ, uploads through the second, while identical choices revert to the conventional coupled association. Successful assignments, together with the resulting data rates, are recorded in the success_throughput array.

Two experiments refined the analysis. First, mobility scenarios group UEs by speed and update their associations on the fly, allowing the model to log handover frequency, packet loss, and latency as functions of velocity. Second, a transmit-power sweep recomputes each UE's consumption and derives bits-per-watt efficiency to expose the power–efficiency trade-off. The dominant operations—dual sorting and repeated capacity checks yield a computational cost of $O(N^2)$, while memory use is driven by the path-loss, scheduling, and results tables.

5 Simulation Environment

This section presents an overview of the details of the simulated network structure and its associated parameters. It is essential to highlight that both the topology and the dataset guiding the simulation setup were sourced from the DeepMIMO platform. This platform serves as a valuable resource, offering the necessary infrastructure to shape and execute the experiments effectively. More specifically, a HetNet 5G MIMO network setup is shown on 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, there is a total of 18 BSs installed, named BS1 through BS18, all standing at a height of 6 meters. Along the main street, there are 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 BS5 and BS7.

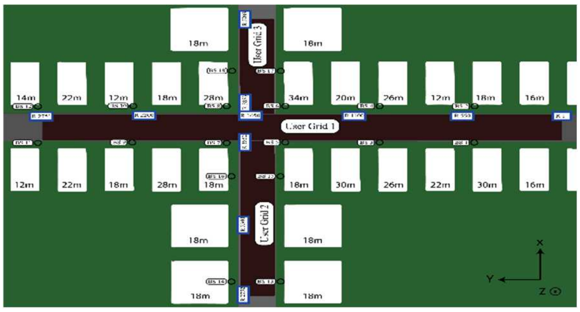

Fig.1. General topology of simulated network.

In the second street, BS13 to BS18 are strategically positioned to maintain stable coverage. 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, a 52-meter separation exists 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, three distinct User Grids (UG) – UG1, UG2, and UG3 can accommodate up to 1,184,923 UEs. With a strategic placement approach, 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, specific areas have been designated for 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, three setups including 180, 360, and 724 UEs, were conducted, all while maintaining consistent UE power of 20 dBm. A summary of these network parameters is provided in Table 1.

Table 1. 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))

In bandwidth allocation scenarios, each UE is randomly assigned to one of the services outlined in Table 2, where the downstream and upstream demands per service are presented.

Table 2. 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

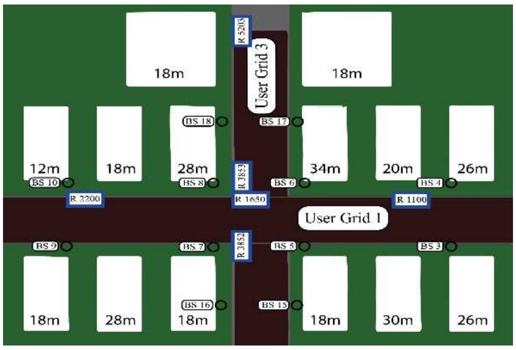

Fig.2. Topology of first simulations.

Also, another experiment is conducted, with Fig. 3 illustrating 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 that were made.

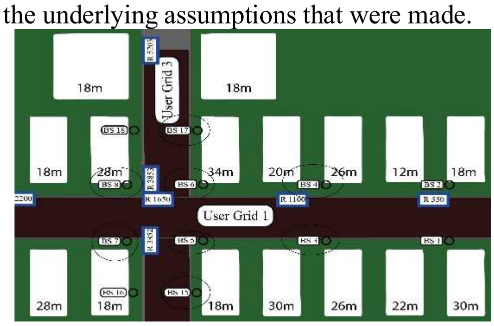

Fig.3. Topology of 905UEs simulations only.

DUDe technology is employed, to ensure equitable resource distribution across antennas while achieving optimal performance. Notably, this approach diverges from previous research by incorporating a MIMO system, where each BS is equipped with 64 antennas. To highlight this point, every mentioned antenna is connected to a UE. This setup allows UEs to connect to multiple antennas, enhancing system performance. The primary 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 60 GHz, the Number of 5G NR resource blocks is 60 and 5G Subcarrier spacing in kHz is 120. Finally, it is crucial to regard that all performance figures averaged over 1000 independent runs in MATLAB, providing a robust estimate of expected behavior under varied conditions.

6 Performance Evaluation

This section delves into the simulation setup and analyzes the conclusions drawn from them, aiming to validate the initial research on the subject. To conduct these experiments, three separate datasheets were generated, each corresponding to scenarios with 362, 543, 724 and 905 UEs. Also, in the scenario involving 905 UEs, the alternative topology described earlier in Fig. 2 was implemented. These UEs are placed within the, previously analyzed, network topology, leveraging the nrpathloss function in Matlab to ensure random yet evenly distributed placements. Specifically, a one-meter distance between each UE is maintained, to prevent overlapping. Additionally, it was investigated how varying UE mobility affected handover frequency, packet loss, and latency under different speed levels, showing increased network stress as UE density rose. And finally, the last scenario focused on analyzing power consumption and energy efficiency across varying transmit power levels, revealing how higher UE counts significantly impacted energy efficiency and power usage. Both these scenarios for mobility and power consumption were simulated based on the topology in Fig.3.

6.1 Resource Allocation scenarios

Several factors were considered in SNR calculations, including the transmission power of the antenna and UE (held constant at 20 dBm in the experiments), antenna gain (21dBi for the BS and 0dBi for the UE), the distance between antenna and UE, and noise. Incorporating these elements ensures an accurate assessment of SNR, a crucial metric for determining wireless communication link quality. The antennas possess a fixed bandwidth capacity of 400 MHz. In all scenarios, UEs are assigned to antennas using a two-step procedure. First, SNR is calculated based on each UE's distance from the antennas. Next, available resources (bandwidth capacity) are assessed to determine whether an antenna can accommodate the UE's service. If sufficient resources are available, the UE is connected to the optimal antenna; otherwise, it is connected to the antenna with the highest SNR. This method guarantees satisfactory service for every UE.

Through graph analysis, the detailed performance characteristics of DUDe and DUCo technologies in a MIMO 5G network setting were examined. Trends and patterns observed in the graphical representations provided insights into the efficacy of these technologies in managing network resources and delivering optimal performance. Also, for a better understanding of the bar plots, it is worth mentioning that they depict 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). Visual comparison of the blue (DUDe) and orange (DUCo) bars reveals how these technologies affect bandwidth availability across different base stations.

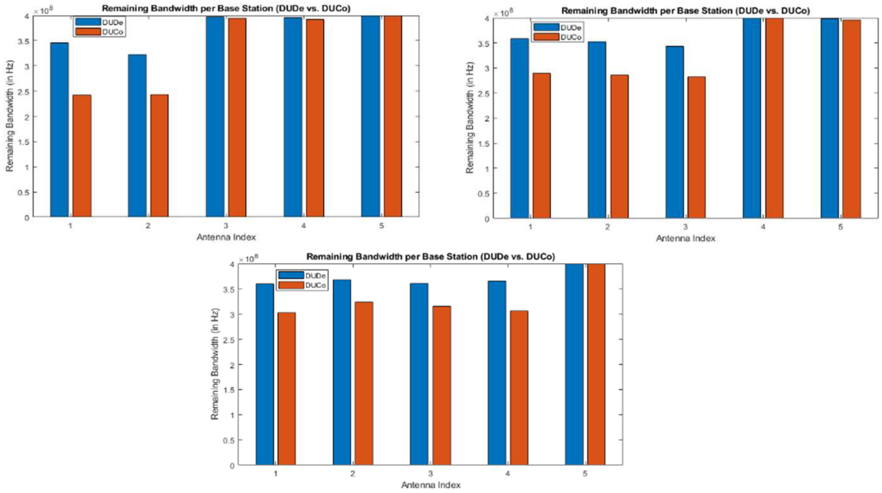

Fig.4. Remaining Bandwidth for 362, 543 and 724 UEs.

In the graph for 724 UEs (bottom bar plot), decoupled technology consistently shows lower bandwidth consumption per antenna compared to coupled technology. The noticeable disparity between the two methods, even at high UE density, suggests that decoupling technology maintains its efficiency advantage in bandwidth utilization..

Also, by examining Fig. 5, It is observed that modifying the network topology, as shown in Fig. 3, does not affect the original hypothesis. DUDe technology consistently demonstrates superior allocation efficiency across BSs compared to DUCo, leading to improved service for both existing and newly added BSs and affirming DUDe's effectiveness in optimizing network performance.

Across all of these 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.

It is important to note also, the observed efficiency of DUDe technology becomes increasingly evident as the network scales. As the number of UEs increases, the ability of DUDe to maintain a more balanced distribution of resources across the network further supports its robustness in high-density environments. Even when accounting for variations in BS performance, the consistency of DUDe in providing higher bandwidth availability across scenarios indicates its capacity to adapt to different network demands without a significant loss in efficiency. This adaptability makes DUDe particularly valuable in real-world deployments where dynamic user behavior and changing traffic patterns require networks to respond fluidly while maintaining performance and resource availability. Through these insights, the results not only validate the proposed algorithm but also emphasize DUDe’s potential to become a key mechanism for optimizing resource allocation in the evolving 5G landscape.

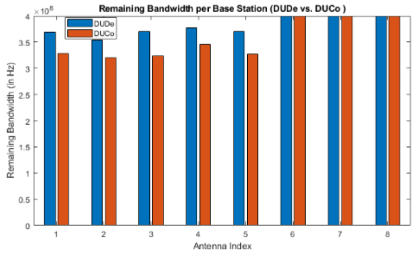

Fig.5. Remaining Bandwidth for 905 UEs.

6.2 Scenarios for the Impact of User Population on Mobility and Energy Efficiency

In this set of experiments, analyzing the impact of varying UE densities on mobility, energy efficiency, and overall network performance. In the analysis of high mobility scenarios and energy efficiency under various transmit power levels, the results offer critical insights into network behavior, especially when scaling up the number of UEs from 362 to 905. By considering the effects of user mobility on handover frequency, packet loss, and latency, and examining the energy efficiency with respect to different transmit power levels, meaningful conclusions for network performance optimization were extracted.

Firstly, the impact of varying mobility speeds on handover frequency, packet loss, and latency was examined. With an increase in the number of UEs from 362 to 905 as seen in Fig.6, the overall trends in these metrics remained consistent, but the values became more pronounced due to the denser user environment. In case of 362 UEs (first bar plot), the handover frequency increased with speed, ranging from approximately 0.8 handovers at 3 km/h to over 20 handovers at 100 km/h. This reflects how higher mobility leads to more frequent handovers as users move rapidly between base stations. For 543 UEs, the handover frequency shows an even steeper gradient compared to 362 UEs, emphasizing the additional burden that a higher UE density places on the network.

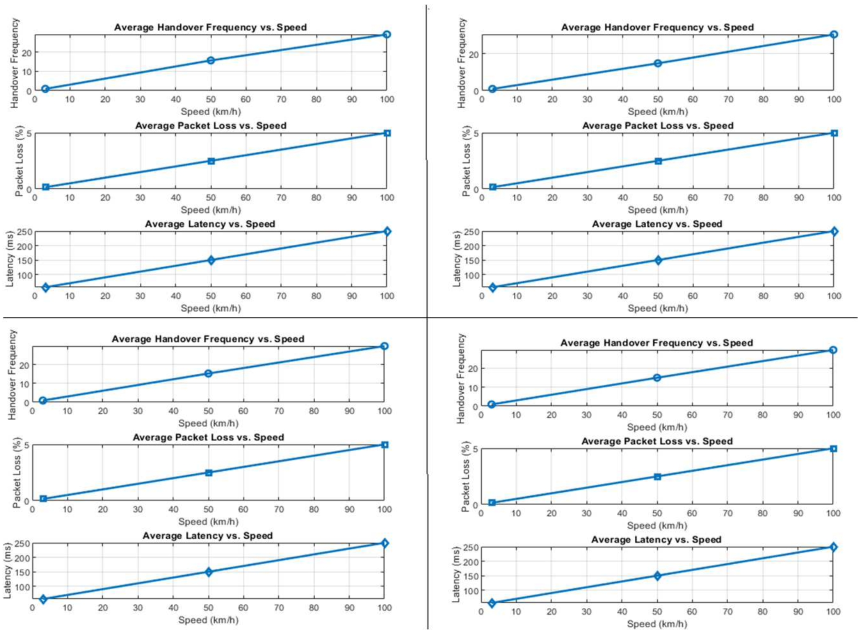

Fig.6. Mobility experiments for 362, 543, 724 and 905 UEs.

Similarly, packet loss increased with speed, as seen in the bottom bar graphs, where packet loss grew from 0% to 3 km/h to 5% at 100 km/h. The effect of adding more UEs resulted in an even higher packet loss at the upper speed levels, indicating that as UE density increases, the likelihood of packet collisions or dropped connections grows due to the heightened network load. Latency, the third key metric, also demonstrated a linear increase with speed, rising from around 50 ms at low speeds to 250 ms at high speeds. The 543 UE configuration saw more severe latency spikes, illustrating the challenge of maintaining low-latency services in densely populated mobile networks. In experiments with 724 and 905 UEs (bottom right bar graph) the results demonstrate consistent trends across different speeds. Handover frequency increases proportionally with speed, reaching its highest levels at 100 km/h. Packet loss also follows a steady upward trajectory as speed rises, indicating that maintaining reliable connectivity becomes more challenging at higher mobility speeds. Latency, a critical factor for quality of service, exhibits an increase with higher speeds, underscoring the impact of mobility on network performance.

In continuation, the study examined the relationship between transmit power, energy efficiency, and power consumption, as you can show in Fig 7. By increasing the number of UEs from 362 to 543, the findings showed an impact on energy efficiency, particularly under high power levels. In addition, energy efficiency, measured in bits per second per watt (bps/W), decreased as transmit power increased. At a transmit power of 45 dBm, energy efficiency peaked at approximately 1.2 x 10^5 bps/W, while at 50 dBm, it dropped to about 3 x 10^4 bps/W. This sharp decline highlights how increasing transmit power does not always lead to proportional gains in network performance, especially when the user density increases to 543 UEs. The additional load from more users stresses the network, causing energy efficiency to degrade more rapidly.

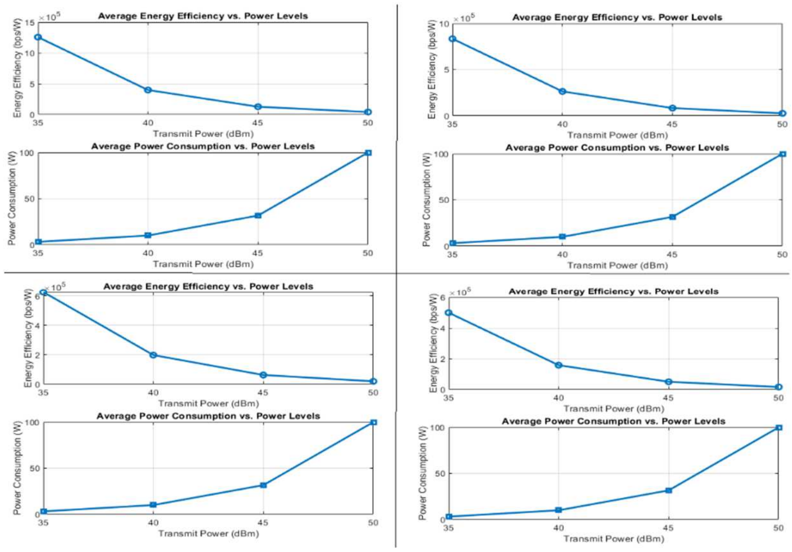

Fig.7. Energy and Power Consumption for 362, 543, 724 and 905 UEs

Power consumption followed an expected trend: as transmit power increased, so did total power usage. Power consumption surged from around 3 W at 35 dBm to 100 W at 50 dBm. With 543 UEs (right top bar graph), the total power required to maintain the network grows significantly, demonstrating that more users not only strain network capacity but also require substantial power resources, especially at higher transmission levels. This insight reinforces the importance of balancing power efficiency with network capacity in dense deployments. Additionally, the results for 724 and 905 UEs(right and left bottom bar graphs) indicate a decrease in energy efficiency as transmit power increases, similar to the findings from lower UE scenarios. However, the gap between the transmit power levels becomes even more significant in higher density environments. The energy efficiency continues to decline sharply as the transmit power level rises to 50 dBm, suggesting that higher UE densities lead to increased network stress and decreased efficiency. Power consumption, as expected, rises with higher transmit power, and the scenario with 905 UEs experiences the steepest increase in power consumption. This indicates that in ultra-dense network conditions, the challenge of maintaining a balance between power efficiency and network performance becomes more pronounced, especially as the transmit power increases. These results reinforce the importance of optimizing energy efficiency and managing power consumption, particularly in high-density scenarios where network resources are heavily taxed. In summary, the introduction of 543 UEs into these experiments underscores the challenges of managing high-density networks. As user mobility increases, network performance degrades in terms of handover frequency, packet loss, and latency. Similarly, while boosting transmit power can support more users, it comes at the cost of reduced energy efficiency and higher power consumption.

The figures provided illustrate these key findings visually, confirming that optimizing network configurations is vital to managing the complex trade-offs between performance, energy consumption, and user density. This escalation in resource demands underscores the need for more refined resource management strategies as user density increases. Moreover, the decline in energy efficiency with rising transmit power levels, particularly when transitioning from 45 dBm to 50 dBm, reinforces the importance of carefully balancing power allocation to avoid diminishing returns. These findings collectively emphasize that managing high-density networks not only requires addressing mobility challenges but also demands careful consideration of energy efficiency, especially as the network scales. Through these observations, the necessity for dynamic, scalable solutions in future network configurations becomes evident, paving the way for more adaptive and efficient resource allocation in increasingly dense 5G environments.

7 Conclusion and Future Work

This research has demonstrated the significant advantages of employing DUDe techniques in resource allocation for 5G MIMO HetNets, particularly in scenarios with varying user densities and mobility patterns. Through a series of experiments, it became clear that DUDe offers substantial improvements over traditional coupling methods. Specifically, DUDe consistently achieves more efficient bandwidth utilization, ensuring that the available network resources are allocated in a way that maximizes capacity while maintaining service quality. This efficiency was evident across all UE density scenarios, from 362 to 905, where DUDe not only reduced bandwidth consumption but also allowed for more balanced and effective load distribution among base stations.

The analysis of user mobility revealed another crucial benefit of DUDe. As user movement increases—reflected in higher speeds and greater handover frequency—traditional network management approaches tend to struggle with maintaining low latency and minimizing packet loss. However, DUDe proved to be more resilient in these challenging conditions. Even with increasing handover rates and the strain that mobility places on the network, DUDe managed to keep performance degradation under control, maintaining more stable connections and better overall service quality compared to coupled systems. This finding underscores the versatility of DUDe in dynamic environments where users are frequently on the move.

In addition to mobility, the exploration of energy efficiency across varying transmit power levels added further depth to the findings. While increasing transmit power is typically associated with better network performance, it comes at the cost of reduced energy efficiency. The experiments showed that as transmit power increased, the energy efficiency of the network declined more rapidly, especially as user density grew. DUDe, however, was able to mitigate this effect by better managing the allocation of resources, demonstrating that it is not only about boosting power but about intelligently distributing it where it is needed most. This ability to balance energy consumption with network performance is especially critical in today's 5G landscape, where sustainability and energy efficiency are becoming key concerns.

Overall, the findings from this research highlight the potential of DUDe to address several of the core challenges faced by modern 5G networks. Unlike traditional approaches, which often fail to dynamically adapt to varying network demands, DUDe provides a more flexible, adaptive framework capable of managing the complexities introduced by high user density, mobility, and energy constraints.

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 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. Furthermore, 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, will benchmark the current DUDe-MIMO baseline against data-driven resource-allocation methods, including deep-reinforcement-learning schedulers and established heuristic schemes for user grouping and power control. It will also couple the physical-layer model with an application-layer traffic trace that reflects the bursty interaction patterns of mobile-learning platforms, allowing latency and uplink continuity to be evaluated under realistic load. Finally, we will investigate possible deployment scenarios like a smart classroom in outdoor fieldwork DUDe and 5G MIMO can provide a stable and cheap network access.

Lastly, another goal, is to explore resource allocation optimization in 5G MIMO DUDe HetNets using the Hungarian and minimum cost flow algorithms, which have already been investigated in 5G MIMO (non-DUDe) HetNets [20], [21]. This positions DUDe as a valuable solution in optimizing network performance in a way that is both scalable and sustainable, offering a forward-looking approach to meeting the demands of future wireless communication systems.

7.1 Acknowledgment

The research project was supported by the Hellenic Foundation for Research and Innovation (H.F.R.I.) under the "2nd Call for H.F.R.I. Research Projects to support Faculty Members & Researchers" (Project Number: 02440).

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