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Dynamic Resource Allocation in Future Cellular Networks: DUDe, MIMO, and Beyond

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Abstract

Resource allocation in 5G and beyond networks remains a demanding problem, largely driven by the rising need for higher data rates, reliable communication, and large-scale device connectivity. This chapter examines approaches that combine Downlink(DL)/Uplink(UL) Decoupling (DUDe) with Multiple-Input-Multiple-Output (MIMO) systems to improve spectral usage and reduce energy consumption. DUDe is used to separate UL and DL associations so that User Equipment (UE) can connect to the most suitable Base Station (BS) for each direction, while MIMO techniques contribute additional spatial degrees of freedom through multiplexing and beamforming. The analysis also incorporates machine learning models that predict UE behavior and assist in adaptive decision-making, together with game-theoretic frameworks that coordinate UE association and resource competition in dense deployments. By bringing these elements together, the chapter outlines how future cellular systems can support more efficient and responsive resource management under realistic mobility and traffic conditions.

Keywords: Resource allocation, Downlink Uplink Decoupling (DUDe), Multi-Input Multi-Output (MIMO), Artificial intelligence-driven optimization, 5G and beyond networks.

1. Introduction

Mobile communication systems have changed drastically in the last years, evolving from networks built almost exclusively for voice services to infrastructures that now sustain high resolution media, interactive applications, and an increasing number of connected devices. As 5G networks continue to improve and interest in the next generation increases, expectations for mobile systems are rising. Modern deployments must serve large and diverse UE populations, each with different requirements for throughput, latency, reliability, and energy consumption [1, 2]. As a result, resource management has become more important, since performance now depends on both the amount of spectrum and how well it is allocated when conditions change. Resource Allocation (RA) determines how bandwidth, transmit power, and spatial resources are shared among UEs and Base Stations (BSs). Modern networks increasingly use Heterogeneous Network (HetNet) layouts, where macro BSs operate alongside smaller, low-power nodes. While such architectures offer significantly improved coverage and capacity, they also introduce new complications: UE association becomes more difficult, interference changes with local activity, and traffic can shift quickly between layers. Methods designed for more uniform networks often struggle with this level of variation.

One development that has received growing attention is Downlink/Uplink Decoupling (DUDe). Instead of forcing a device to rely on the same BS for both directions of communication, DUDe allows UL and DL associations to be chosen independently. This flexibility acknowledges that the two links experience different propagation and interference conditions. In practice, DUDe can relieve congested macro cells, improve uplink links via nearby small cells, and reduce unnecessary transmit power, which is especially useful in dense and mobile settings [3]. In parallel, Massive Multiple-Input Multiple-Output (Massive MIMO) has become an important development of technology. By equipping BSs with large antenna arrays, networks gain the ability to serve many UEs simultaneously through spatial multiplexing and to concentrate energy more effectively through beamforming. These advantages, however, do not happen automatically. They depend on how UEs are grouped, how resources are split, and how associations are managed across layers of the network. RA choices therefore play a decisive role in determining whether Massive MIMO systems deliver their expected improvements in practice.

Alongside architectural changes, algorithmic tools have become a key part of modern RA strategies. Machine Learning (ML) methods can identify patterns in UE mobility, traffic patterns, and channel fluctuations, allowing the network to predict short-term changes instead of only reacting to them. Predictive models help avoid inefficient allocations and reduce the need for fixed, rule-based behavior, especially in environments where conditions shift faster than traditional optimization methods can adapt [4]. At the same time, Game Theory (GT) offers a framework for analyzing how UEs or BSs behave when their objectives differ or even conflict. By modeling these interactions directly, GT can be used to study stable operating points, explore the trade-off between fairness and throughput, and design mechanisms that promote cooperation when centralized control is limited or impractical [5, 6]. This technique is particularly useful in dense deployments where many decisions must be made locally but still influence network-wide performance.

The material presented in this chapter brings these technologies together: HetNets, DUDe, Massive MIMO, ML, and GT to provide a coherent view of RA in current and emerging cellular systems. The discussion builds on earlier work, including studies on energy efficient operation, UL/DL asymmetry, and predictive models for UE distribution. Together, these efforts show how decoupled access can change uplink behavior, how MIMO benefits from balanced UE grouping, how ML supports adaptive decisions, and how GT can guide interactions among competing UEs [7]. Even though 5G and future networks are technically complex, they also create opportunities to rethink many long standing RA assumptions. Therefore, this work has a twofold purpose: to clarify the central challenges in RA today, and to position the contributions within ongoing progress in network design and performance optimization. The following sections outline key concepts, review related literature, and describe the models and methods used in this research.

2. Background and State of the Art

Recent studies have investigated how more flexible association mechanisms can tackle these challenges. Traditional coupled access, which forces both UL and DL traffic to follow the same BS, often results in suboptimal performance in HetNets. This constraint has increased interest in DUDe, which allows devices to use different base stations for uplink and downlink transmissions. The concept has been studied extensively as a means to rebalance traffic across network tiers, reduce UL transmission power, and improve spectral efficiency in dense mobile environments. State of the art investigations examine DUDe not only as an architectural feature but also as a key enabler for more adaptive and energy efficient resource allocation schemes under dynamic network conditions [8-10].

In parallel, improvements in radio technology have transformed how resources can be managed. Massive MIMO, which equips BSs with large antenna arrays, significantly increases spectral efficiency by supporting many UEs simultaneously through spatial multiplexing and beamforming. As a result, resource allocation must also consider UE placement across beams, the link between resources and traffic load, and the energy impact of using large antenna arrays. Research in this area increasingly focuses on finding strategies that utilize the spatial capabilities of Massive MIMO while controlling energy consumption and maintaining stable performance under mobility.

Beyond architectural and physical-layer developments, modern networks now increasingly use data driven algorithmic intelligence. ML has become a useful tool for predicting UE mobility, traffic demand, and identifying patterns in channel behavior that are not easily captured by fixed rules. ML based resource allocation frameworks aim to support networks that anticipate changes rather than simply reacting to them, particularly in environments where UE movement and service requirements fluctuate over short time periods. The literature includes both supervised and reinforcement learning approaches that adjust association, bandwidth allocation, and power control in real time [11-14].

Complementing ML, GT offers conceptual and mathematical structures for analyzing how multiple decision makers interact when competing for limited resources. In wireless systems, GT has been used to model UE association, power control, and spectrum allocation, linking individual goals to overall network performance. Different formulations such as Stackelberg models, Nash bargaining, Mean-Field Games, and Potential Game offer various perspectives on fairness, stability, scalability, and distributed optimization. These models are widely studied for designing resource allocation schemes that still work well when centralized coordination becomes difficult or expensive [15, 16].

The current state of the art highlights how network architecture, spatial processing, prediction, and strategic modeling are increasingly combined. DUDe changes how UL and DL resources can be assigned; Massive MIMO expands the spatial dimension of resource management; ML provides adaptability and foresight; and GT offers structured principles for balancing competing interests within large systems. These directions provide the basis for the remainder of the chapter, where each theme is examined in more detail and the contributions of this work are introduced in the corresponding sections.

3. System Model and Key Assumptions

For clarity and consistency, the next part introduces the system model and assumptions that will be used across the following sections. The model includes key aspects of current 5G networks but remains general so it can be used without linking the discussion to any particular simulation tool or mathematical framework. Its purpose is to give the reader a clear understanding of the network environment in which association decisions, spatial processing, strategic interactions, and predictive algorithms operate.

The system under consideration is a HetNet cellular network, where a traditional macro layer is assisted by additional tiers of micro and pico BSs. These layers are deployed to increase coverage in sparse regions and to provide additional capacity in dense ones. UEs may therefore find themselves within range of multiple candidate BSs, each offering different potential advantages depending on distance, load, and radio conditions. This multi-tier architecture creates a natural setting for flexible association strategies, as the optimal choice for a UE is not necessarily determined by the strongest DL signal alone.

A key characteristic of the model is that UL and DL behave differently. For DL, the primary limitation is interference and the capacity of the serving BS, whereas in the UL direction, the transmission power of the UE device plays a crucial role. Because these two approaches respond differently to distance, loss, and cell load, the assumption that a UE must connect to the same BS for both directions is not always optimal. The model therefore allows UL and DL to be considered independently, allowing for the understanding of DUDe as an architectural option [17, 18].

The system also incorporates Massive MIMO capabilities at selected BSs, most often at the macro layer. These stations are equipped with large antenna arrays that can shape directional beams and serve multiple UEs simultaneously. While the full details of the antenna processing are not required here, it is important to understand that spatial resources form an additional dimension of the allocation problem. Network performance depends not only on how many UEs connect to a BS but also on how effectively its antenna resources are distributed among those UEs. In this sense, Massive MIMO introduces opportunities for increased capacity but also requires careful management of UE distribution.

UE mobility is another critical component. Whether UEs move slowly within indoor environments or rapidly across outdoor areas, their positions influence which BSs can serve them effectively and how long good radio conditions can be maintained. The system therefore assumes that mobility can be variable and, in some situations, highly dynamic. This assumption is important when considering algorithmic approaches such as ML, which can benefit from predicting changes in UE position, and GT, which must account for the fact that resource competition evolves over time. In addition, modern networks must balance performance with sustainability, and resource allocation decisions often influence energy consumption at both the BS and UE device levels. The system assumes that energy usage is a necessary performance indicator and that UL and DL decisions can affect it differently.

Finally, although a variety of concepts and algorithms are discussed in this chapter, the core system model is kept technology-agnostic. It can be implemented in environments like DeepMIMO, used with standardized propagation models, or combined with mobility datasets, yet it is not tied to any single platform or dataset. These assumptions describe a modern, flexible, and dynamic network environment. Multiple layers of BSs coexist; UL and DL behave differently; spatial resources influence performance; UEs are mobile; and energy efficiency matters. This model reflects the challenges faced by real 5G systems and provides the fundamentals for understanding the resource allocation strategies presented later on. The following chapters will be built upon this framework to examine the methods and technologies that were studied [19, 20].

4. Downlink/Uplink Decoupling in HetNet Networks

DUDe has attracted more interest as mobile networks move toward denser, more demanding HetNet deployments. Traditional UE association usually assumes that the same base station serves both the DL and UL transmissions. This coupled approach simplifies design, but it doesn't satisfy modern HetNets, where base stations can vary widely in coverage, transmit power, antenna setup, and traffic load. Because UL and DL are limited by different factors, for example, BSs transmit at much higher power than UEs, and UEs experience widely varying pathloss, many studies state that the traditional coupled access tends to create inefficiencies, especially in dense urban deployments.

The central idea behind DUDe is to treat the UL and DL as independent association decisions. This allows a UE to use the cell with the strongest or most reliable DL for reception, while sending UL data through a nearer and less congested cell, improving uplink efficiency. Studies on DUDe report that decoupling can improve load balancing across HetNet levels. By directing more uplink traffic to small cells, macro base stations face less UL load, leaving more capacity for wide area DL coverage and helping the network respond appropriately to the UE's demands. Several works also highlight that DUDe can reduce UE transmit power, since UEs no longer need to reach a distant macro BS for UL communication, which in turn supports longer device battery life and lowers interference across the network.

Another thread of the state-of-the-art discussion concerns the interaction between DUDe and mobility. Because UEs move through areas served by cells of varying size and capacity, the benefits of decoupling are more pronounced when the association mechanism can adapt to changing link conditions without causing instability. Prior research shows that DUDe smooths UL performance for fast-moving UEs and mitigates the sharp UL degradation that often occurs when UEs transition between macro and small-cell coverage areas. In addition, DUDe is increasingly examined in combination with advanced antenna technologies such as MIMO, where the decoupling of UL and DL can make spatial resources more effective by distributing UEs more evenly across antenna domains.

These results highlight DUDe as a crucial technology for next generation resource allocation. Once UL and DL association are decoupled, allocation decisions can be fine-tuned, supporting energy-aware scheduling and more adaptive policies that better match the demands in modern networks. It also creates opportunities for hybrid approaches that blend decoupling with predictive algorithms and strategic decision-making topics that will be explored in later sections.

The contribution of this research on DUDe builds on a common simulation framework for HetNet 5G networks, where Macro, Micro and Pico BSs coexist in the same coverage area and serve a large number of UEs. In all cases, the focus is on how UE association and UL-DL pairing affect energy consumption, bandwidth usage and UE distribution across the different tiers of a HetNet. The same family of scenarios is used to study two complementary aspects: energy efficiency under decoupled access and the impact of DUDe on bandwidth and UE allocation in dense deployments.

At the start of research, DUDe is evaluated as an energy-aware association mechanism operating under strict transmit-power limits at the UE side [21]. The network is represented as an urban and a rural topology, each populated with fixed numbers of Macro, Micro, and Pico BSs configured with realistic transmit powers, antenna heights, and gains, following the propagation assumptions of the 3rd Generation Partnership Project (3GPP) TR 38.901 [22] specification. Rather than presenting the full mathematical formulation, the analysis relies on a well-established pathloss model to estimate signal attenuation between each BS and UE, from which the corresponding UL and DL Signal-to-Noise Ratios (SNRs) are obtained. Using these SNR values and a maximum UL transmit-power constraint, two association rules are compared: traditional Downlink/Uplink Coupling (DUCo), where both directions are served by the same BS, and DUDe, where UL traffic may attach to a different, typically nearer, small cell while the DL remains anchored to the BS offering the strongest received power. To operationalize this comparison, a simulation chain generates random UE positions within the coverage region, evaluates pathloss and SNR for every BS-UE pair, and computes per-UE transmit and received power under both DUCo and DUDe. Energy consumption is assessed by aggregating the UL transmit energy required to maintain a consistent quality of service under each association policy, along with the corresponding reception requirements at the base-station side. The setup holds traffic, propagation, and power limits constant across both schemes, so the impact of the association method can be evaluated on its own.

In addition, the following equations summarize how the simulation links pathloss, SNR, bandwidth demand, and energy efficiency.

Pathloss PLij determines the received power for the link between UEi and BSj. The received power expressed in the following Eq. (1):

$$P_{\mathrm{r,\,ij}}\,[dBm] = P_{\mathrm{t}}\,[dBm] + G_{\mathrm{t}}\,[dBi] + G_{\mathrm{r}}\,[dBi] - PL_{\mathrm{ij}}\,[dB] \tag{1}$$

After that the simulation convert Pr,ij to linear units with Eq. (2):

$$\gamma_{\mathrm{ij}} = P_{\mathrm{r,\,ij}} / (N_0 \cdot B_{\mathrm{ij}}) \tag{2}$$

Where here the N_0 denotes the noise power spectral density and B_{ij} denotes the allocated bandwidth. Furthermore, given in some experiments a target rate Ri, bandwidth demand follows the Shannon–Hartley guideline as seen in the Eq.(3):

$$B_{\mathrm{ij}} = R_{\mathrm{i}} / log_2(1 + \gamma_{\mathrm{ij}}) \tag{3}$$

Lower SNR increases the bandwidth needed to support the same rate. Energy efficiency is expressed in bits per Joule as the total served rate divided by the total consumed power across base stations and UEs. The expression of this is shown in the following Eq. (4):

$$\eta = (\textstyle\sum_{\mathrm{i}} R_{\mathrm{i}}) / (\sum_{\mathrm{j}} (P_{\mathrm{t,\,j}}(DL)/\xi_{\mathrm{j}} + P\_c,_{\mathrm{j}}) + \sum_{\mathrm{i}} (UL)) \tag{4}$$

The $P_{t,j}$(DL)is the BS downlink transmit power, ξ_j is the power-amplifier efficiency, $P\_c_{,j}$ is the BS circuit power, and $P_{t,j}$(UL) is the UE uplink transmit power. This definition links association decisions to energy cost, since DUDe can reduce uplink transmit power by shifting uplink connections toward closer cells while keeping the downlink anchored to strong coverage when needed.

Across both the urban and rural deployments, DUDe consistently exhibits lower energy consumption than DUCo. The primary reason is that many UL connections migrate from distant Macro BSs to closer Micro and Pico sites, which require substantially less transmit power to achieve the same SNR target. This redistribution of UL traffic also alleviates load on the macro layer and supports more energy-conscious operation of high-power BSs, as illustrated in Figure 1.

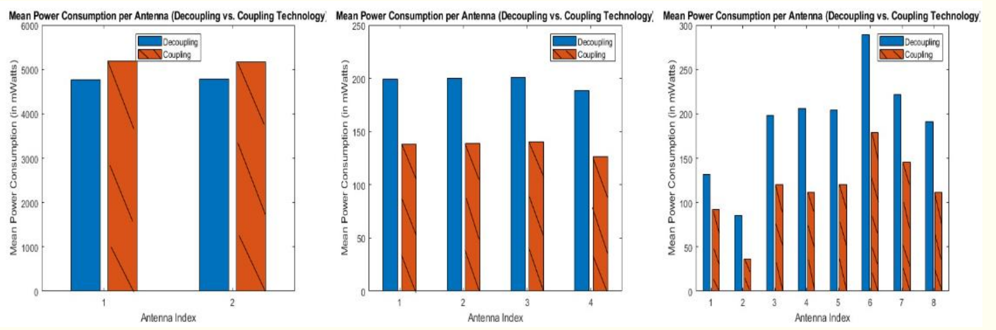

Figure 1 Comparison Energy Consumption per Macro, Micro and Pico BS under DUCo and DUDe

Another contribution in the field of DUDe [23] shifts attention from energy considerations to resource allocation and UE distribution. In this study, a HetNet 5G network composed of Macro, Micro, and Pico BSs is again examined, but the emphasis is placed on bandwidth consumption at the macro layer and the distribution of UEs across the different tiers when DUDe is activated. The association logic relies on the same foundational elements pathloss, SNR, and tier-specific capacity constraints yet the primary performance indicators become the bandwidth utilized at each BS and the number of UEs admitted within each tier. DUCo continues to serve as the baseline configuration, assigning every UE to a single BS for both UL and DL, while DUDe enables the UL to be handled by a different, typically smaller, cell, with the DL remaining anchored to the macro station that provides the strongest received signal.

In the bandwidth-oriented experiments, each UE is assigned a service profile with specific UL and DL rate requirements, such as web browsing, video streaming or more demanding applications. Using the Shannon-Hartley capacity relationship as a guideline rather than a strict optimization tool, the simulator derives the bandwidth that each BS must allocate to satisfy these demands under the measured SNR values. The important point for the reader is that the bandwidth assigned to the Macro BSs is finite and comparable to realistic mid-band 5G deployments; as more UEs attach to macro sites under DUCo, the available bandwidth per UE decreases and the macro layer approaches its capacity limit. Under DUDe, a substantial fraction of UL traffic is migrated to Micro and Pico BSs, which relieves the macro layer from part of the burden and allows more UEs to be served without exceeding its bandwidth budget. The comparison between the two association schemes therefore reveals not only better bandwidth utilization(Figure 2) but also a more balanced distribution of UEs (Figure 3).

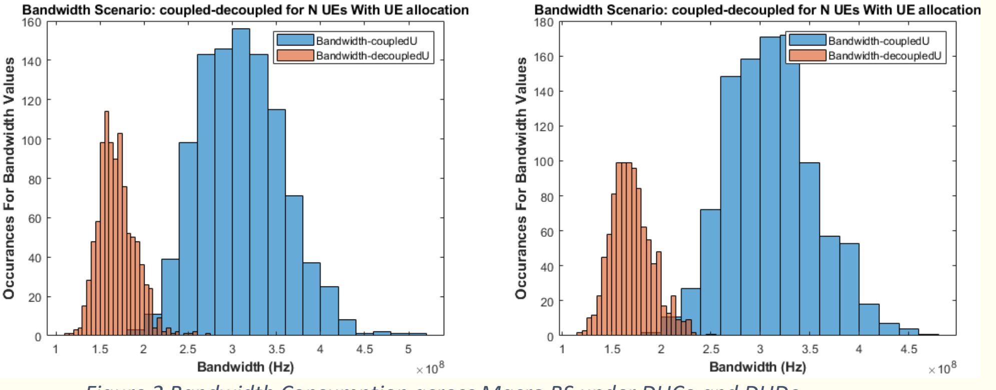

Figure 2 Bandwidth Consumption across Macro BS under DUCo and DUDe

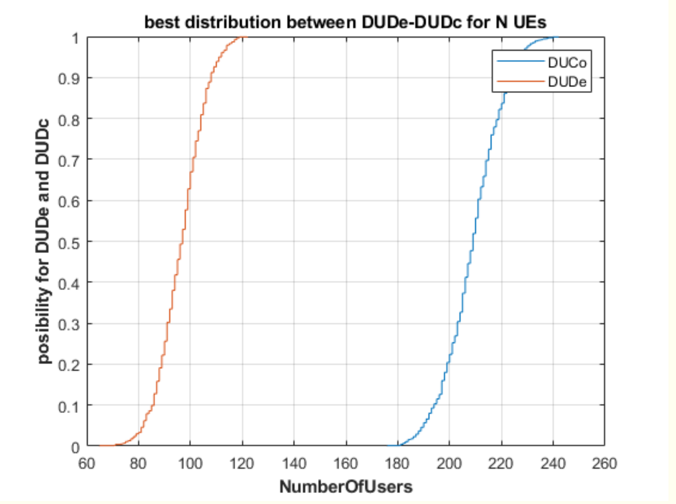

Figure 3 UEs distribution under DUDe and DUCo for Marco BS

These two research efforts provide a coherent picture of DUDe as a practical mechanism for improving the behavior of HetNet 5G networks without changing the underlying physical layer or antenna configuration. The energy-oriented study demonstrates that by decoupling UL and DL associations and exploiting the proximity of small cells, it is possible to reduce UE transmit energy and alleviate the load on high-power macro infrastructure. The complementary bandwidth-oriented investigation shows that the same decoupling logic can be used to preserve scarce macro-layer bandwidth and to avoid over-concentration of UEs in a single tier, resulting in more graceful scaling as the number of active UEs increases.

5. Resource Allocation and Performance Challenges in MIMO-Based 5G Networks

MIMO has become a defining feature of modern wireless systems, mainly because multiple antenna setups let a network serve more UEs, transfer higher data rates, and keep links more stable. In 5G, it is treated as part of the core architecture rather than an add-on, since it makes practical use of spatial degrees through beamforming and spatial multiplexing. This means a BS can concentrate its energy toward selected users, limit interference toward others, and support more diverse service even when the environment is crowded. However, these gains come with practical disadvantages that affect resource allocation. Multiple antenna processing increases computational effort and often increases energy usage, while both UL and DL require extra signaling and more demanding channel-state acquisition and tracking. In real deployments, performance depends heavily on where users are located, how they move, the local propagation conditions, and the traffic they generate. As shown in the literature, results can vary widely with user density, antenna placement, and SNR, so the benefits of MIMO should not be treated uniformly across an entire network.

Moreover, MIMO performance is also tightly linked to UL quality. Since UL SNR affects how accurately the channel can be estimated, weak uplink conditions can limit spatial processing even when the DL signal looks strong. This imbalance between UL and DL has pushed many MIMO oriented studies toward more flexible association, mobility-aware prediction, and scheduling that responds to traffic patterns and uses spatial resources where they matter most. The literature also stresses a practical balancing act between UE density and antenna load: if too few users are served, spatial multiplexing is not fully used, while an overloaded array may struggle to separate users cleanly and performance starts to drop.

Further recent work also points to energy consumption as a growing concern. While MIMO can deliver more throughput from the same spectrum, running large antenna arrays and their signal processing adds a noticeable power cost. For this reason, several studies look at ideas such as selective antenna activation, better UL–DL coordination, and adaptive association to keep energy overhead under control. Overall, the central idea from the literature is that MIMO resource management needs to capture spatial gains without driving energy consumption upward, using approaches that connect where UEs are located with how the antenna resources are used in an adaptive and practical way.

The first relevant study [24] focuses on how multiple antenna 5G deployments behave as UE load changes, how service demand varies across the network and how user locations follow more realistic patterns. The evaluation is built on an urban scenario generated using the DeepMIMO dataset, and it focuses on how spatial diversity, UE distribution, and resource usage interact in a multiple antenna system. In this setting, DUDe is not treated as the core technology, but rather as a useful mechanism for showing how strongly MIMO outcomes can depend on UL channel conditions and where UEs are positioned in the.

The results show that the remaining bandwidth at each BS depends heavily on whether UL traffic is guided through directions that fit the antenna array well. As the number of UEs increases from 362 to 905, the multiple antenna setup retains noticeably more bandwidth when UL connections align with antenna elements that provide stronger channel quality. This highlights a basic point about MIMO in practice: spatial resources are used effectively only when the UE distribution matches the array geometry in a way that the system can exploit. The bandwidth trends that capture this sensitivity are represented in Figure 4:

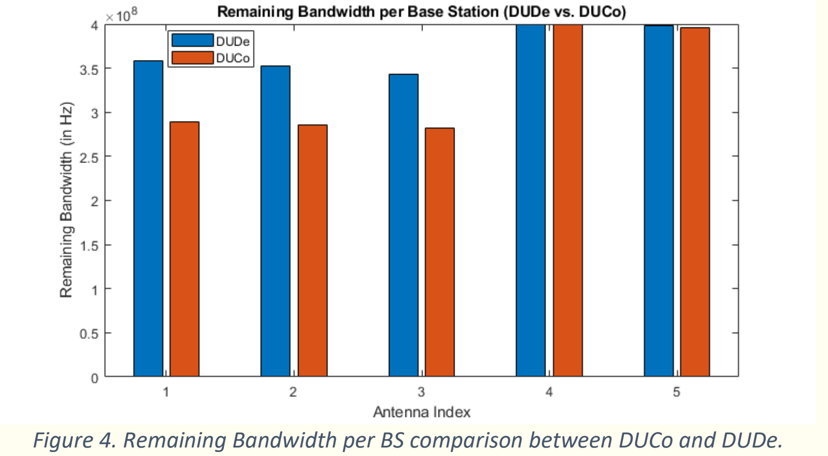

Figure 4. Remaining Bandwidth per BS comparison between DUCo and DUDe.

The mobility experiments in [25], further strengthen by highlighting how UE motion interacts with MIMO spatial processing. As UE velocity increases, handover frequency and packet loss escalate rapidly when UL and DL remain tied to the same serving element, especially in dense regions where sharp spatial transitions occur. When the UL is allowed to follow the direction of the antenna with better channel conditions, mobility causes less disruption and latency increases more smoothly. Overall, the results reinforce that MIMO performance depends strongly on uplink quality and on how UEs are positioned relative to the antenna geometry. The key mobility trends are summarized in Figures 5–6:

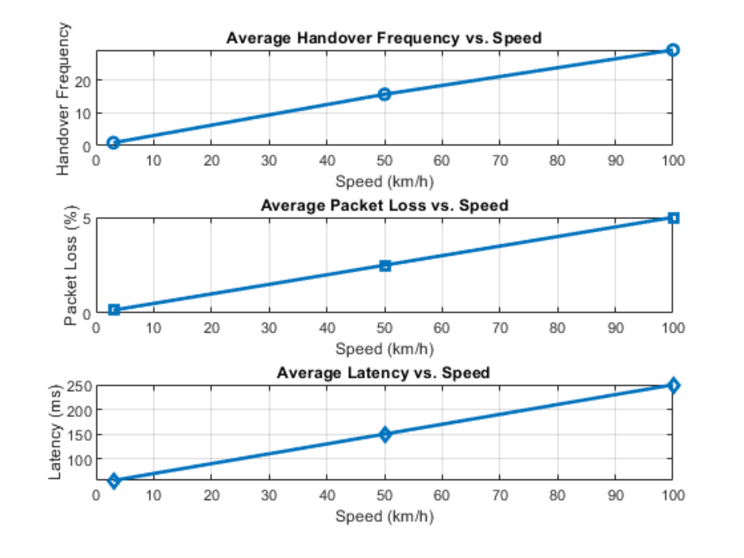

Figure 5. Performance in comparison to speed MIMO.

Energy efficiency observations support these findings. As the UE load rises, the power needed to maintain uplink connectivity depends strongly on each UE's distance to the serving BS and the quality of its channel to the antenna array. When uplink links are pointed towards antenna directions with better conditions, transmit power tends to spread more evenly across UEs and the total energy consumption is lower. This again suggests that MIMO behavior is driven more by spatial geometry and link quality than by antenna count alone. These results are illustrated in Figure 6:

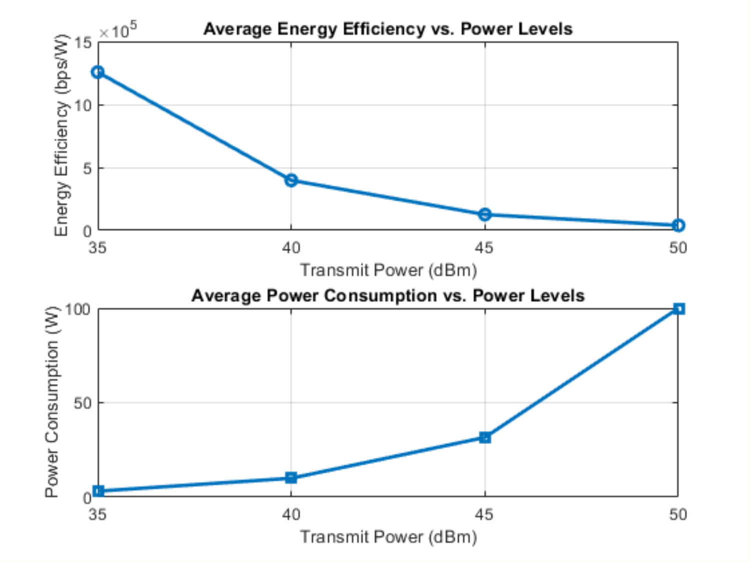

Figure 6. Energy Efficiency and Power Consumption for MIMO.

In conclusion, these observations offer a more detailed view of how multiple antenna 5G systems behave when spatial diversity, channel conditions and UE mobility converge. The studies support the idea that the effectiveness of MIMO depends not simply on expanding antenna arrays, but on how well UE distribution, UL channel quality and resource allocation strategies align with the system's geometric structure. Bandwidth utilization, mobility robustness, energy consumption and UE distribution all interact closely MIMO operation, providing a starting point for future work that combines spatial processing with predictive and optimization focused techniques.

6. Machine Learning for Adaptive Resource Allocation in 5G and Beyond Networks

ML has become increasingly important in wireless systems because 5G, and the early direction of 6G, operate in environments that are dense, heterogeneous, and dynamic. Traditional approaches often lose effectiveness when confronted with rapidly shifting traffic patterns, HetNet service demands, and mobility-induced channel variations. As radio access networks evolve into multi-layered topologies and integrate massive MIMO arrays, optimization problems that once appeared manageable now involve thousands of interacting UEs, fluctuating propagation conditions, and a variety of hardware states that scale over time. ML offers an alternative that learns patterns from data, captures nonlinear behavior without fixed rules, and makes fast decisions with less computation than repeatedly solving complex optimization problems.

Within this domain, Reinforcement Learning (RL) has become more widely used. RL treats network control as a series of decisions made under uncertainty, where a BS or a controller chooses actions and adjusts them over time based on observed traffic load, interference levels, and UE distribution. Early studies showed that RL can outperform standard heuristic methods in tasks such as small cell sleep scheduling, interference management, and traffic steering. Later work expanded these ideas to larger systems, introducing deep RL architectures capable of encoding complex network states and learning energy- or throughput-aware policies. The appeal of RL lies in its capacity for continuous adaptation, particularly when channel conditions or mobility patterns evolve unpredictably. In multi-layer and HetNet 5G deployments where idle and active states of macro and small cells must be coordinated RL has repeatedly shown that data-driven decision-making can reduce energy consumption without sacrificing latency or service guarantees.

Graph Neural Networks (GNNs) have transformed learning-based resource allocation into multi-antenna systems. Wireless networks naturally form graph structures consisting of UEs, BSs, and, in some cases, antenna panels or resource blocks. Interference, geometry, pathloss, and connectivity follow relational patterns that GNNs can express more efficiently than conventional neural models. While homogeneous GNNs were first used for tasks such as power control and beamforming, more sophisticated HetNet GNNs now distinguish between node types, enabling joint optimization that simultaneously considers UE association, per-antenna power distribution, and the interplay among multiple BSs. Their ability to approximate classical optimization methods such as WMMSE in a single inference step has positioned GNNs as a powerful tool for real-time operation, offering substantial reductions in computational effort while retaining near-optimal performance.

Across literature, two trends stand out. First, ML-based methods usually perform better than fixed resource allocation schemes when network conditions change quickly. Second, the most reliable results often come from hybrid designs, where learning is supported by basic domain knowledge or by signals produced by classical optimization methods. This has led research toward combining prediction with practical HetNet conditions, user mobility, and multiple antenna operation. The aim is not only better performance, but also a better balance between energy usage, fairness, and scalability under realistic constraints. the contributions discussed in this section focus on two related directions in ML-based resource allocation: using reinforcement learning for dynamic energy control in HetNet 5G/6G systems and using graph neural networks in MIMO-based HetNets to jointly handle UE association and power allocation. Together, these works show how ML can be used directly in network control, supporting decisions that are more adaptive, scalable, and efficient for next-generation wireless systems.

The first contribution studies RL for dynamic energy management in 5G and later networks, with a focus on deciding which base stations should stay active as traffic demand and user mobility change. It proposes a deep RL approach that can switch cell states (active, idle, or sleep), based on real-time indicators such as load, latency, interference, and energy use. Instead of using fixed sleep schedules or simple heuristics, the RL agent learns its policy through interaction with a simulated network that includes daily traffic variation, HetNet deployments, and multi-cell interference.

The simulations show that the RL-driven policy significantly reduces overall energy consumption while maintaining acceptable latency and minimizing service level agreement violations. Under peak-hour, off-peak, and variable-load scenarios, the RL strategy consistently outperforms baseline policies, activating only the minimum number of cells required to satisfy service constraints. This behavior highlights the role of RL in anticipating load transitions and adapting cell states before inefficient configurations emerge. Representative outcomes can be seen in Figures 7-10.

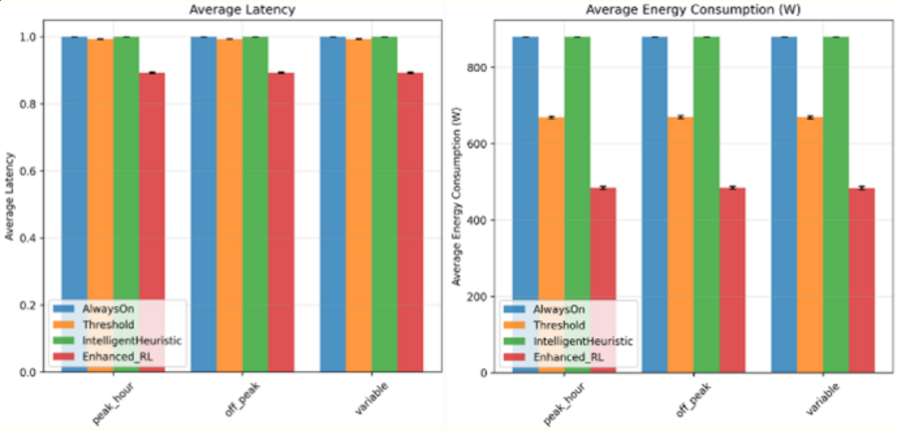

Figure 7. Average Latency and Energy Consumption across RL models.

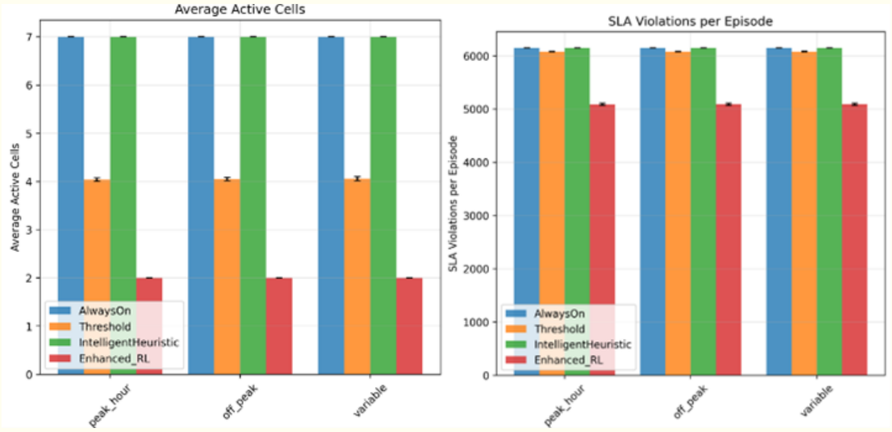

Figure 8. Average Active Cells and Violations per RL model.

These results demonstrate the growing importance of RL for intelligent power-state control in next-generation networks, particularly as energy consumption becomes a central design constraint in future 6G systems.

The second contribution applies ML from a structural perspective, using a HetNet graph neural network to jointly predict UE association and antenna-level power allocation in 5G MIMO HetNet networks. Unlike conventional iterative optimizers, which treat association and power as separate sequential tasks, the proposed model represents BSs, UEs, and antenna elements as distinct node type-aware message passing to embed their relationships into a unified graph. This enables the network to produce both association decisions and per-resource-block power fractions in a single inference step. The evaluation, conducted on a DeepMIMO-based urban deployment containing 5,400 UEs and five BSs, shows that the HetNet GNN achieves more than 85% of the throughput of the WMMSE teacher algorithm while requiring only a single forward pass. Although fairness and low-percentile rates fall slightly below the teacher, the model delivers substantial gains over the baseline heuristic and performs inference in milliseconds, making it suitable for real-time adaptation in dense deployments.

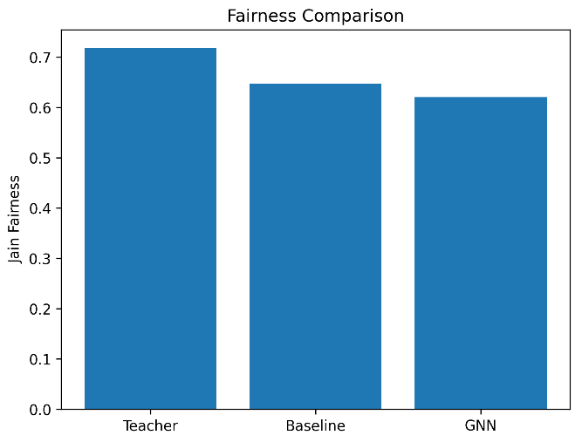

Figure 9. Jain's Fairness Index for RL.

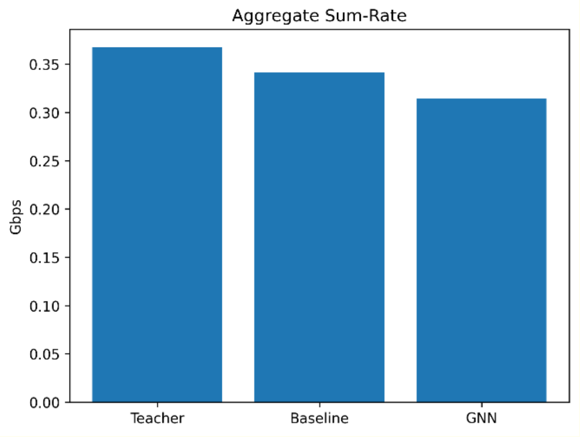

Figure 10. Aggregate Sum-Rate for RL.

Overall, the results support the use of graph-based learning in HetNets, since the network can be described naturally as connected nodes. By using geometry, channel conditions, antenna context, and interference relations together, the model can deliver strong allocations without the delay of running full optimization at every step.

The RL framework and the HetNet GNN describe two practical ways to update resource allocation for 5G and beyond. RL is mainly used for control over time, it learns how the network should adjust its actions as load, interference, and mobility change. On the contrary, the HetNet GNN targets fast decisions, it uses the network's structure to produce appropriate association and power patterns on demand. Both reflect the same reality: future networks will be larger, more dynamic, and more difficult to manage with fixed rules or slow centralized optimization.

7. Game-Theoretic Resource Allocation in 5G MIMO Networks

GT has become a common way to describe wireless resource management in 5G MIMO systems. Dense deployments and mobility make channel conditions change quickly, so allocation must work under uncertainty. Many studies therefore favor adaptive mechanisms over rigid optimization rules, especially when UEs and BSs influence each other. GT provides a clear framework for this, since decisions are interdependent and results emerge through competition, coordination, or equilibrium.

Previous studies focused on applying classical game models leader-follower formulations, cooperative bargaining schemes, mean-field approximations and potential-driven equilibria to static or semi-static MIMO networks. These methods demonstrated that distributed decision making can achieve many of the benefits of centralized scheduling while keeping signaling lower overhead. However, performance often remained highly sensitive to UE mobility, because of fast changes in distance, pathloss, and SNR can reshape the utility values faster than the game can reach a stable outcome. In practice, once users move away from the initial conditions, fairness, energy efficiency, and bandwidth utilization may start to vary in ways that are difficult to control. Over time, the literature has split into two broad responses to this problem. Some work stays within the game-theoretic layer and tries to make the games themselves more practical under mobility. Other work treats mobility as something that should be anticipated rather than absorbed and introduces prediction, so that the key quantities that drive the utilities (distance, pathloss, SNR) can be estimated ahead of time. This view is especially useful in MIMO settings, where small geometric changes can quickly alter spatial separability and effective antenna gains. Instead of adjusting after performance has already dropped, a predictive allocator can act on the geometry that is likely to hold in the next interval. The emphasis therefore moves from reacting to fading and movement to making allocation choices early enough to limit their impact.

Within this setting, two studies are useful for showing how GT-based methods can be applied in mobile 5G MIMO networks [26, 27]. The first presents a common testbed for four well-known approaches (Stackelberg, Nash bargaining, mean-field games, and potential games), under continuous UE mobility, where channel-related inputs are refreshed at every scheduling step. The same mobility traces and the same inputs (distance, pathloss, and data-rate conditions) are used across all four methods, so differences in outcomes can be traced back to the game structure rather than to the scenario itself. The comparison makes the contrasts clear. Some schemes tend to gather UEs toward the most favorable antennas, while others distribute users more broadly across the available cells or beams. The objectives also differ, certain formulations lean toward fairness, while some prioritize throughput and others try to balance fairness with energy efficiency. Under mobility, these patterns become more visible because the UE geometry changes every interval, forcing each method to respond to a shifting spatial situation. The experiments show that performance is shaped not only by antenna capability or total bandwidth, but by how each game reacts to changes in distance, SNR, and user velocity. The main trends are illustrated in Figures 11–12.

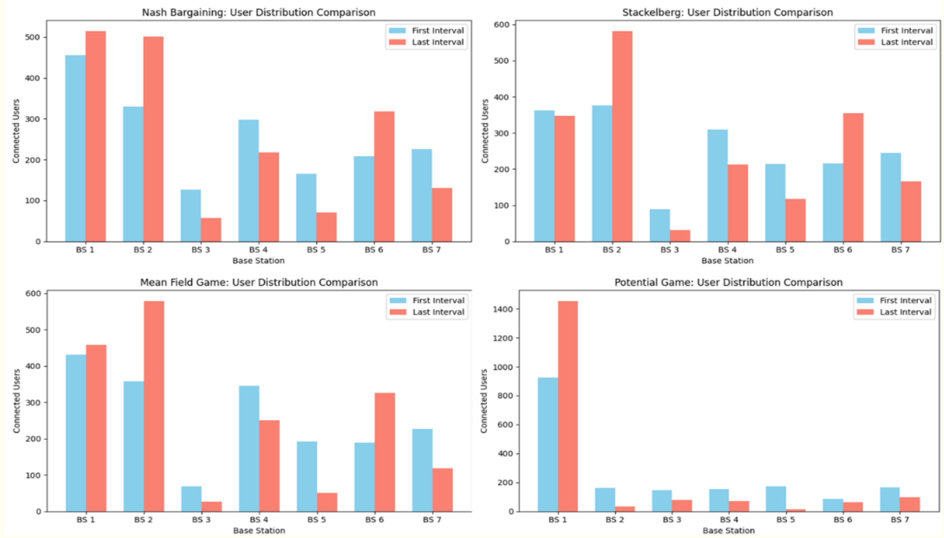

Figure 11. Game Theory Algorithm UE Distribution Comparison between BSs.

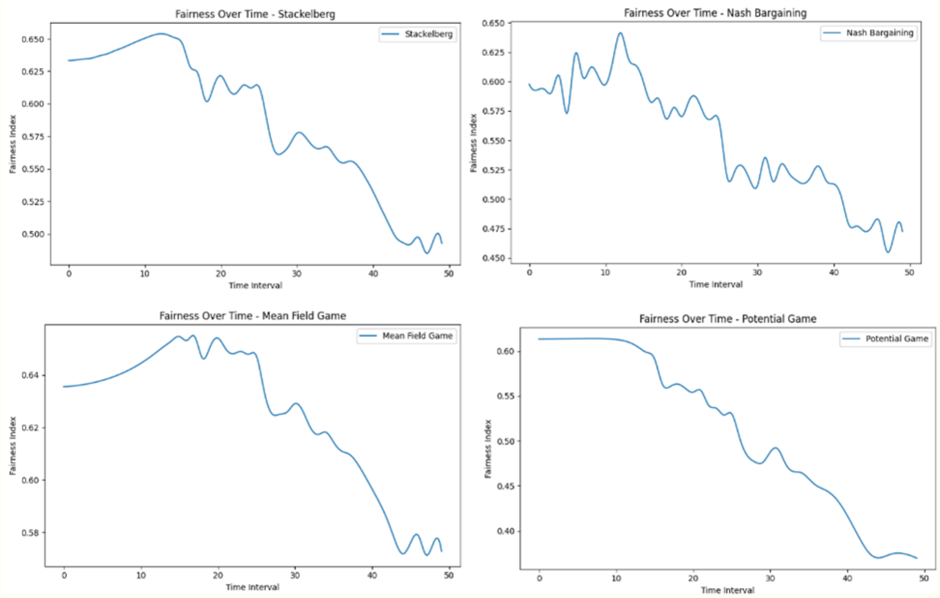

Figure 12. Fairness Across Game Theory Models.

The results of the research underscore how MIMO-topology sensitivity, UE dynamics, and spatial load distribution collectively determine the practical suitability of each algorithm. No single method dominates all metrics; each excels under specific system priorities. The analysis therefore provides a rigorous baseline: a realistic, mobility-aware comparison of four major game-theoretic resource allocation frameworks in a 5G MIMO environment.

Building on this baseline, the second research provides a predictive, mobility-aware reinforcement learning mechanism that augments these same games with short-horizon foresight. Instead of allocating resources based solely on current measurements, a lightweight neural model forecasts UE positions and channel quality one interval into the future. These predictions are then used to update the payoff values given to each game, so the resulting equilibria are based on the geometry expected in the next interval rather than the geometry observed in the past. This leads to a control process that is more stable and more forward-looking, where allocations converge faster, sudden bursts of handovers are reduced, and throughput improves because strategic choices better match the SNR that is likely to occur. Some of the performance metrics are shown in Figures 13–14.

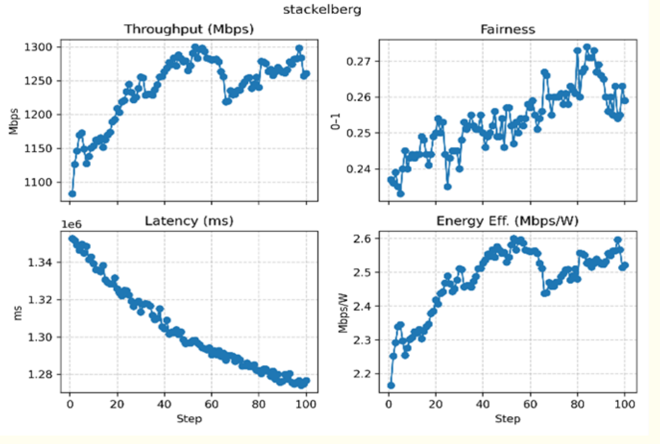

Figure 13. Stackelberg Metrics.

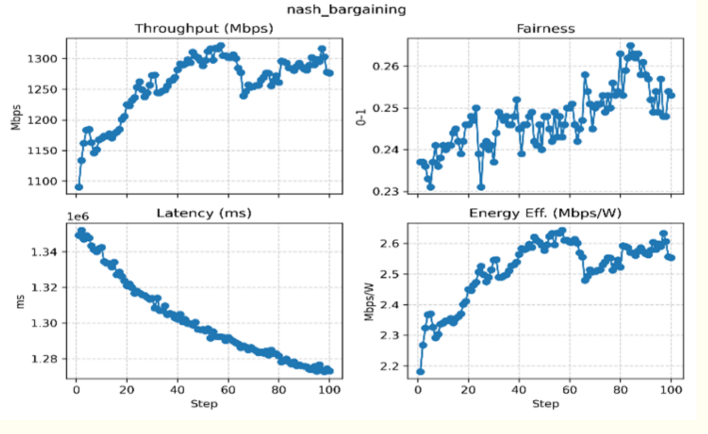

Figure 14. Nash Bargaining Metrics.

The predictive layer helps the games behave more steadily under mobility, reducing sudden swings by smoothing how the system moves from one state to the next. This matters in dense MIMO deployments, where antenna selection and spatial effects can change quickly and interact in complicated ways. Game-theoretic models can describe how UEs compete or cooperate, but predictive reinforcement learning adds information about what is likely to happen next, so the decisions stay sensible as geometry shifts. Together, they support a resource allocation approach that is more efficient, and scalable for future networks.

In summary, these findings show that GT still provides a strong way to think about strategic resource allocation, but also that its performance in MIMO settings improves when mobility awareness and spatial prediction are added. As 5G moves toward denser deployments, higher mobility, and more diverse HetNet demands, combining predictive intelligence with decentralized decision rules can help balance network performance, without depending on a single, heavy centralized scheduler.

Conclusion

This chapter shows that resource allocation in modern cellular networks is driven less by fixed design choices and more by conditions that change from one moment to the next. Mobility, uneven traffic demand, and shifting interference mean that a solution that looks reasonable in a static setting can quickly become inefficient once the geometry and load of the network evolve. For this reason, the chapter's main themes should be seen as responses to the same underlying challenge: allocation decisions must remain effective under continual change.

Each theme contributes a distinct part of the overall picture. DUDe highlights that uplink and downlink constraints are not symmetric, and that treating association as a single coupled choice can waste resources and energy in heterogeneous deployments. Massive MIMO demonstrates that spatial processing offers major gains, but only when user distribution and scheduling align with the spatial structure of the environment; simply adding antennas does not guarantee consistent improvement. Game-theoretic methods provide a disciplined way to represent competition and cooperation when decisions are distributed across many actors, yet their stability can be fragile when mobility reshapes channel conditions faster than equilibria can settle. ML-based approaches address this gap by learning patterns in traffic and movement, enabling decisions to be guided by expected short-term conditions rather than delayed observations.

Overall, the chapter leads to a clear endpoint and also points to next steps. Future wireless systems will require resource management methods that adapt fast, stay stable under frequent updates, and scale in dense, heterogeneous deployments. A natural extension is to integrate RL, so the association policy adjusts UE–BS UL/DL coupling over time based on mobility, traffic demand, and channel conditions. The same framework can then be evaluated in 6G oriented scenarios, where cell free massive MIMO, denser layouts, and higher carrier frequencies reshape interference and handover behavior. RIS-enabled networks provide another research path, since association can interact with RIS phase control and beamforming; a joint design can aim at higher energy efficiency and throughput while keeping control latency bounded. Stronger validation should rely on larger traces, mixed indoor–outdoor settings, and hardware-aware power models to maintain reproducibility and improve relevance to real deployments.

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