State of the Art Analysis of Resource Allocation Techniques in 5G MIMO Networks

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***Abstract*— The industry is shifting from 4G to 5G, which promises a tenfold increase in data throughput. However, 5G is about much more than simply higher bandwidth. 5G is basically a re-architecture of network infrastructure that incorporates a number of significant technology advancements. One important aspect of 5G networks is the Resource Allocation (RA), where many promising technologies are implemented, like Multi-User Multiple-Input Multiple-Output (MU-MIMO) and Downlink and Uplink Decoupling (DUDe) and many new technologies like Machine Learning (ML) and Game Theory (GT) must be investigated. This paper presents state of art research for RA using MU-MIMO, DUDe, ML and GT. The above will be the base for proposing guidance for effective RA algorithm design and implementation for 5G and beyond networks.**

Keywords—5G, MIMO, DUDe, Machine Learning, Game Theory, Resource Allocation

I. INTRODUCTION

Mobile networks [1], like the Internet, have seen significant developments during the last 40 years. In the previous two generations, voice and text were accessible, but 3G marked the transition to internet connectivity, with speeds estimated in the hundreds of kbps. The industry is shifting from 4G (which enables speeds of a few megabits per second) to 5G, which promises a tenfold increase in data throughput. However, 5G is much more than simply higher bandwidth. 5G is basically a re-architecture of network infrastructure that incorporates a number of significant technology advancements and places it on a path to allow for much greater expansion. 5G's promise is simply the shift from a single network access (broadband connection) to a larger range of edge devices and services, similar to how 3G signalled the transfer from voice to broadband. 5G is expected to improve immersive user interfaces (e.g., AR/VR), task-oriented applications (e.g., public safety, autonomous cars), and the Internet of Things (IoT). Because these scenarios will include anything from domestic appliances to automation technologies and to self-driving cars. Moreover, 5G will allow not just humans to access the Internet via their smartphones, but also a huge number of autonomous objects to control their own systems. More than just boosting bandwidth or lowering latency for individual users is required to support these services. And 5G will bring a whole new edge network design is required.

The architectural requirements are ambitious, as indicated by three functional categories: a) Massive IoT support, such as ultra-low power (battery life of 10 years or more), ultra-low complexity (10s of bits per second), and ultra-high device density (1 m devices per km2). b) Mission-Critical Control may provide ultra-high availability (greater than 99.999 percent or "five nines"), ultra-low latency (less than 1 ms), and extreme agility (up to 100 km/h). c) For Enhanced Mobile Broadband, extremely high data rates (multi-gigabit per second peak, sustained speeds of 100+ Mbps) and large capacity (10 Tbps aggregate throughput per km2) are required.

All of this means that there is no one, comprehensive definition of 5G, just as there is no single, comprehensive definition of the Internet. It's a complex and dynamic system regulated by a set of rules that provide all sides plenty of room to manoeuvre. One important aspect of 5G networks is the Resource Allocation (RA), where many promising technologies are implemented, like Multi-User Multiple-Input Multiple-Output (MU-MIMO) and Downlink and Uplink Decoupling (DUDe) and many new technologies like Machine Learning (ML) and Game Theory (GT) must be investigated.

Motivation of this paper is the project ERA5G-Beyond (Efficient Resource Allocation in 5G and Beyond Networks) [7] which will incorporate MU-MIMO, DUDe, ML, and GT in order to implement innovative RA mechanisms for 5G and beyond networks. This paper presents state of art research for RA using MU-MIMO, DUDe, ML, and GT. The above will be the base for proposing guidance for effective RA algorithm design, identifying practical problems, and reflecting on and analysing state-of-the-art critical applications in the context of ERA5G-Beyond project.

The following is how the paper is structured. We present ERA5G-Beyond project in section II. Section III presents state of art research for RA based on MU-MIMO and section IV presents state of art research for RA based on DUDe. In section V state of art research for RA using ML is presented. Moreover, section VI presents state of art research for RA using GT. Finally, section VII concludes with our findings and, the direction that should be followed in the future.

II. ERA5G-BEYOND

The main objective of the ERA5G-Beyond project is to study, design, develop and evaluate technologies and techniques towards efficient resource allocation in 5G and Beyond Networks. The project goal consists of two different phases: In the first phase, the project will examine the possibilities of current promising technologies, such as MU-MIMO and DUDe. The project will investigate possible efficiency shortcomings or loopholes that limit their performance, and it will propose new mechanisms/algorithms or improve the existing ones targeting at achieving efficient allocation of physical resources in Heterogeneous Networks (HetNets). In the second phase, the project will apply techniques inspired by ML and GT to the proposed mechanisms/algorithms in order to add prediction models and user fairness, which will, in turn, refine/optimize the performance of MU-MIMO and DUDe in terms of resource allocation, throughput, spectral efficiency, and energy consumption. Starting from the DUDe technology, recent 5G HetNet architecture has shifted from the current Network-Centric (NC) model and moved towards a pioneering User-Centric (UC) one. This new user-oriented network model promises improved connectivity among network subscribers and their assigned BSs inside dense HetNet deployments. The main aspect that differentiates traditional homogeneous networks and heterogeneous ones is the fact that a HetNet decouples the original network into two networks, Uplink (UL) and Downlink (DL), and considers them as two separate networks with different system models, each one with their respective architecture. The ERA5G-Beyond project will take advantage of the above and offer the ability for a User Equipment (UE) to possibly connect to different BSs in the UL and DL direction, thus providing increased freedom over managing all possible UE-BS associations for the decoupled networks. The notion of HetNets envisions improving current macrocell infrastructures by installing small cell BSs in areas along macro cell borders, offering users improved coverage and throughput near the cell borders [8].

Regarding the technology of MU-MIMO, the massive growth of applied MIMO systems calls for higher data rates and opens the road for a set of applications never seen before. Recent research on wireless communication systems has enabled the design of MIMO systems that support multiple users. These communication systems are usually referred to as Multi-User MIMOs. MU-MIMO systems present high tolerance to propagation limitations, such as antenna correlation and channel rank loss (unlike Single-User MIMO systems), which make MU-MIMO systems an ideal technological candidate for future wireless standards. MIMO is used within MU-MIMO communication systems in multiuser channels and cellular systems, in order to allow for channel spatial sharing by several users. The ERA5G-Beyond project will use the MU-MIMO technology and integrate it in 5G and Beyond HetNets in order to boost the communication system capacity and enhance the reliability of the communication links, taking advantage of the several diversity schemes. ERA5G-Beyond project goal is to take advantage of multiple antennas on both ends (user and BS) of the communication link, so as to significantly improve the achieved spectral efficiency of the communication system, as well as the achieved reliability of the communication link [9].

The application of ML with increasing hardware performance and data availability is blossoming, penetrating and delivering solutions to more and more areas of our daily lives as well as computer science. ML enables us to address dynamic problems, such as the real-time distribution of network resources, and make valid decisions based on data, even if the data are incomplete, noisy or even contradictory. That is why ML techniques have been proposed by several researchers (e.g., [10], [11]) as a crucial technology to facilitate 5G+ networks and services. The ML techniques vary according to the type of data available, and the specifications of the problem addressed. Data mining and big data analysis can be used to process the vast amount of data generated by the users, their devices, and the network services discovering specific trends and patterns. Self-organizing maps applied to cellular networks [12] have been proposed to dynamically shape the connectivity of the network to the prospective demands. Deep learning with Artificial Neural Networks (ANNs) can be used to automate all management [13], operation, and maintenance network tasks, limiting direct human intervention as much as possible. Several ML optimization methods [14] have been proposed to configure network parameters such as delay, loss rate, link Signal-to-Noise Ratio (SNR), etc. Further ML methods have been proposed to confront issues concerning traffic prediction, routing and classification, congestion control, resource and fault management, Quality of service (QoS) and Quality of Experience (QoE) management, and network security [15]. During the ERA5G-Beyond project we shall evaluate several ML methods with respect to the project data and specifications, aiming to improve the overall performance of the 5G infrastructure. The ERA5G-Beyond project will use notions from GT to model the strategic behaviour of users and network operators and related techniques to assess the performance of resource allocation algorithms. The particular approach that we will employ falls within the interdisciplinary field of Algorithmic Game Theory [17], which studies solution concepts from GT (e.g., Nash equilibria) in terms of computational (complexity of equilibria, best-response dynamics) and economic efficiency (e.g., quantified using the notion of the price of anarchy). This study aims either to define tractable ways for coordination between network operators and users when competing for accessing resources or to evaluate resource allocation in terms of Price of Anarchy, quantifying in this way the effects of strategic behaviour.

III. MU- MIMO State Of the Art

MIMO technology can help with interference reduction, spatial multiplexing, and diversity [3]. As a result, it's been hailed as a crucial strategy for boosting future wireless networks' spectral efficiency. Enhanced MIMO has been used in Long Term Evolution (LTE) to address the International Mobile Telecommunications Advanced (IMT-advanced) rate prerequisites, that include both traditional techniques like precoding, spatial diversity and multiplexing, as well as advanced techniques like MU-MIMO beamforming and Coordinated MultiPoint (CoMP) reception and transmission [4], [5]. MU-MIMO [6], which allocates several simultaneous connections for the same bandwidth sources, can greatly improve system performance. The remaining of this paragraph presents the current state of the art in the area of MU-MIMO RA. The researchers of [51] present a new solution for packet forwarding across several carriers based on the multi-user MIMO technique. For spatial multiplexing of numerous operators on the smallest available radio resource unit, they use antenna arrays. Between the joint operators and the service providers, they evaluate three distinct service level agreements. In terms of the pre-defined system utility efficiency, the arrangements vary. The accomplishment of equality between operators and the improvement of the network's spectral efficiency are the standards they wish to maintain. In addition, they present innovative techniques for achieving such benefits. Their techniques fully meet service level agreements, which is among the primary goals of a shared network situation, according to simulated data.

In [41], a generic paradigm for resource allocation is presented, in cellular Orthogonal Frequency Division Multiple Access (OFDMA) configurations that takes into account all of these elements of MU-MIMO, as well as a scheduling algorithm for optimal allocation of resources. A resource allocation methodology for a limited-feedback delay-sensitive MU-MIMO broadcast system, is proposed in [42]. Because transmit power and feedback bandwidth are both scarce and interdependent, it's vital to integrate and maximize both resources to meet the delay-QoS requirement. The authors developed a sealed formulation of the average probability of a breach as a function of transmission power of the feedback channel and the length of the codebook for a specific delay requirement using the effective bandwidth theory. Finally, they built an efficient collaborative allocation of resources technique that can dynamically adjust the power of transmission and feedback bandwidth based on the system's characteristics by reducing the overall resource cost.

The authors of [43] investigate the subject of DL sum rate optimization in MU-MIMO systems based on codebooks. They provide a linear equation for said possible sum rate of a MU-MIMO communications network with codebook restricted precoding based on average channels, in which various streams of data are provided to all users, at the same time. Following that, they provide unique, computationally efficient min-max based methods for determining the best beamforming vectors and power control to every beam to maximize the possible sum rate, which they combine to generate an ideal solution. The BS in MU-MIMO serves multiple users simultaneously on the same frequency, according to [44]. The spectral efficiency of DL MU-MIMO is the subject of this paper. The purpose of this study is to increase the communication system's attained spectral efficiency as well as the communication link's accomplished consistency. To maximize the system's spectral utilization, an approach based on DL scheduling and resource allocation is presented. This paper's approach, which takes into account the requests of the users, is to be able to assign a possible user who is in the queue, to the "optimal antenna" depending on their requirements and location, in order to increase the number of supported devices. The study in [56] expands the CF technique towards the situation where antenna arrays, are equipped to both the APs and MSs, offering a beamforming approach that doesn't even need CSI at the MSs by counting on the channel hardening factor. The CF massive MIMO strategy is contrasted with a user-centric (UC) model, in which each MS is serviced by a tiny proportion of APs. Because distant APs have a low SINR, therefore are useless for servicing distant clients. As a result, the UC strategy, although having smaller backhaul cost than the CF strategy, is demonstrated to provide better results and outcomes, when it comes to attainable rate-per-user for the substantial proportion of MSs in the system. Additionally, the authors suggest different power distribution strategies for the UL and DL, where one targeted at optimizing total connection speed and the other geared at increasing the overall equity, within the system.

IV. DUDe State Of the Art

DUDe allows the User Equipment (UE) to connect to a different BSs for DL and UL. According to DUDe technology, each UE creates two lists (one for DL addresses and one for UL addresses) composed of BSs that can be used for association. Each list is sorted according to characteristics like SINR or Path Loss (PL). After preparing the list, each UE tries to connect to the preferred BS. If this BS can deliver the requested Resource Block (RB), a connection between the UE and this BS is created. If there are not enough RBs, the UE tries to connect to the next preferred BS. The above described procedure is carried out in both directions until each UE is connected to a BS. The main idea of DUDe is that it treats DL and UL as two different networks, leading to faster associations and a better user experience. The following of this paragraph presents the current state of the art in the area of DUDe RA. In [52] a DUDe scheme, is suggested, for the equity of a cooperation system, which takes into account both WiFi and LTE performance. In their decoupling model, resource allocation is based on variable spectrum segmentation, allowing for the cohabitation of WiFi and LTE, and customers can share both networks. Furthermore, to ensure that their concept is feasible, they used a Support Vector Machine (SVM) to forecast the overall number of subscribers in a WiFi and LTE cohabitation design, and the results demonstrate that it has a high prediction accuracy while being simple to implement. The suggested DUDe method outperforms the competition in terms of sum throughput, according to simulation data. Due to how effectively resources are allocated, the aggregate throughput of the DUDe system can be nearly double that of the linked association scheme. According to [46], the volume of mobile traffic on networks has increased as the use of mobile phones and IoT equipment has grown. This study investigates a DUDe access mechanism for multiple frequency channels in order to maximize the usage of frequency bands in wireless connections. DUDe is a wireless communication method that makes efficient use of frequencies by linking the UL and DL to separate BS. The authors offer two BS identification methods: SINR-based decoupling with re-association (SBD-RA) and SINR-based decoupling with first-come, first-served (SBD-FCFS). Based on the results obtained from simulations, they indicate that either SBD-FCFS and SBD-RA give increased performance by exploiting bands more effectively than DUDe while being assigned to the same channel, or without employing DUDe.

The 5G cellular network standard will include mmWave-based Small Cell Base Stations (SCBSs) to boost information throughput and capacity of the network, as stated in [47]. An optimization issue is described in [47] for combined UL and DL scheduling and allocation of resources in a dynamic TDD system. The hybrid TDD and user scheduling time fractions are calculated using a generalized fair scheduler. The results of the simulation are provided, which agree with the obtained findings and demonstrate a 17% increase in throughput for some situations, which can be attributed to appropriate resource allocation in most cases. The DUDe approach is further underlined in [48], which claims that it is one of the most promising facilitators for simultaneously optimizing both connections. Furthermore, the growing urge to include mmWave transmissions in future networks expands the possibility for larger capacity. To that end, and in contrast to previous work that has investigated the benefits of using capacity-based multi-association in Ultra-high Frequency (UHF) and millimeter-wave hybrid networks, the benefits of using capacity-based multi-association in (UHF) and millimeter-wave hybrid networks, are investigated. Another example may be found in [49], which states that future network architectures would be more complex and heterogeneous, posing more issues for interference control. DUDe has gained popularity, as it unloads UEs to SCBS and offers a more conducive setting for Device to Device (D2D) communication. The authors of this research examine the use of DUDe in D2D-underlay HetNets and suggest a network sum-rate maximization approach that includes joint cell affiliation, subchannel assignment, and power regulation. The power regulation technique is also used to maximize the network sum-rate while meeting the UE restrictions on the power of transmission and the rate of data.

Authors in [50], present resource allocation and interference mitigation for HetNets with D2D cells at the bottom ranks. Researchers primarily analyse DUDe user association and assess its potential on interference control and network-wide D2D performance enhancement in order to relieve the dead-zone challenge. Secondly, they present a UL Fractional Frequency Reuse (FFR) method in which Sub Bands (SBs) are dynamically selected based on UE volume, eNB density, and small cell ON/OFF switching frequency. The dynamic strategy greatly minimizes the individuals impacted by outages, according to the findings. Then, for concurrent SB Assignment (SA) and RA of CUs, a unique Concatenated Bi-partite Matching (CBM) technique is implemented. Empirical findings reveal that the CBM achieves a similar level of performance to the exhaustive solution while consuming significantly less time. For D2D cells, the CBM is then expanded to include localized mode selection, SA, and RA. Furthermore, they present semi-distributed offline and online techniques in which a D2D-cell can repurpose White-List RBs (WRBs) that are not held by neighbouring SCBS. D2D-cell participants are unaware of intra-cell and inter-cell interference in the first, and evenly transfer their maximum allowable voltage to WRBs in the latter. They use the closeness benefit of D2D UEs to convert D2D sum rate maximization into a symmetrical expression in the latter (DUEs). The online decentralized method is then created by transmitting dual parameters and consistency costs as messages.

V. MACHINE LEARNING STATE OF THE ART

In the 5G and beyond era the network is not static anymore, so ML techniques will help analyse complex networks and distribute network resources in real-time. The main ML techniques investigated are Deep Learning (DL), Reinforcement Learning (RL), Imitation Learning (IL) and Deep Q Learning. There are different approaches based on the above techniques in order to improve RA at 5G networks at [10]. Sun et al. [53] use IL in order to train a deep neural network based on Weighted Minimum Mean Square Error RA algorithm regarding wireless networks that have limited interference. In cloud radio access networks, Xu et al. [54] use reinforcement learning for improving the energy consumption. The data that are determined through the process are the user demand, the on/off modes of radio heads and the current mode. The result is that the proposed DRL controller makes the whole system work as expected with less energy consumption. In cognitive communications, Ferreira et al. [38] use deep State-Action-Reward-State-Action (SARSA) and achieves to reduce the computational resources. This is done by eliminating the number of trials having poor parameters.

Qian Mao in [11] uses a spatiotemporal modelling scheme based on hybrid Deep Learning for traffic prediction in order to optimize the RA of the network. The reason for using the scheme is that some data like traffic load, spectrum usage etc can vary spatially and temporally and constant values cannot be used. The components of the scheme are a Global Stacked Auto Encoder (GSAE), Local Stacked Auto Encoders (LSAEs) and Long Short-term Memory Units (LSTMs).

Another approach for improving RA that has been proposed recently is network slicing, meaning the ability to provide virtual logically independent “slices” of the network. A network slice consists of a set of software Virtual Network Functions (VNFs) that run on a virtual network infrastructure and provide a specific telecommunication service.

At [39] a decision-making model based on semi-Markov decision process (SMDP) is presented and then the N3AC algorithm is designed based on a neural network in order to verify the acceptance of requests from tenants ensuring that the corresponding Service Level Agreements (SLAs) will be satisfied and that the Infrastructure provider will have maximum profit. The authors defend that the most suitable ML approach for RA and efficient resource utilization is RL. The reason behind this is that RL can be deployed without any initial policies and it can adapt to the demands of the network by learning. Some examples are using simulation or synthetic data as datasets in order to determine network throughput, delay or reliability using a RL technique.

At [40] the authors use SL for MIMO Channel estimation and detection. One approach is with a regression model that is used for predicting radio parameters that are associated with specific users. In the case of massive MIMO systems which use a big number of antennas, these models can address the problem of high-dimensional searching. In general, regression analysis estimates the relationship between variables and can be either linear or logistic. Finally, the other approach is Bayesian Learning. The target is to calculate the probability of the target variables based on their inputs. More specifically, the authors estimated the parameters of the channel at the target cell as well as the adjacent using BL techniques. The channel component was modelled by a Gaussians mixture model and then an Expectation Maximization algorithm was used for the result. Finally Based on [15] there are two areas that we need to focus on regarding RA improvement, Call Admission Control (CAC) and Energy efficiency. Call Admission Control (CAC) determines how many calls can be in the system, at a given time. When a new call comes to the network, CAC works as a regulator, deciding if it can be admitted or not. There are some published proposals for optimizing CAC. For example, a CAC function is proposed that relies on predictions as well regarding call dropping probability. Energy Efficiency is the other area that should be improved. The main consequence of high energy consumption is the operator cost, but we also want a greener network. Alsedairy et al. [55] propose a network densification framework. Cloud small cells are deployed instead of regular cells. The difference is that they are smart, meaning that they become available on demand after communication with macrocells. That improves energy consumption. At last, Wang et al. [56] use big data with supervised learning (polynomial regression) for energy optimization in ultra dense cellular networks, defending that their solution can achieve the highest cell throughput while maintaining energy efficiency, compared to conventional approaches.

VI. GAME THEORY STATE OF THE ART

Game Theory provides analytical tools which help us understand the interaction between strategic decision-makers [16]. The reader can find crucial information about central notions and well-established applications in [16], [17], [18]. Luong et al. [19] provide an early literature review of GT and economics applications for RA in 5G networks. In the remainder of the section, we briefly cover recent game-theoretic related work. Various RA schemes have been proposed in the literature, both for 5G and Beyond networks, as well as for traditional networks, where the solution concept is the Nash Equilibrium (NE). Roughly speaking, a NE is a stable state, where no individual can increase their gain, using only their own means. Scutari et al. [20] propose decentralized multiplexing solutions for multipoint-to-multipoint communication, where a set of non-cooperative links are using the same physical resource. They show conditions for which their solutions implement a unique NE. Zappone et al. [21] provide a decentralized power control procedure where the users are modelled as rational agents, all of which aim to maximize their individual energy efficiency and show that best response dynamics converge to a NE.

Sheng et al. [22], focus on emerging new technologies in High-Speed Rail communication, which is connected to the development of 5G networks. They analyze a game where the users (e.g., devices of the train's passengers) compete for the resources from the channel and show the existence of a NE. Feng et al. in [23] focus on massive MIMO and HetNets with backhaul links. They investigate wireless backhaul networks and propose a decentralized scheme for RA between users, which converges in a NE. Grassi et al. [24] focus on the energy efficiency of the uplink in massive MIMO and propose decentralized algorithms, where the participants reach a Generalized Nash Equilibrium, a generalization of the NE notion, where each player's strategies can depend on other players' strategies (see [25], [26]). The techniques are derived from [27] which focuses on similar problems.

Yu et al. in [28] propose an extension of the 5G C-RAN, to improve spectrum efficiency and support heavy-duty applications in vehicular networks. RA in cloudlets of this system is formulated as a non-cooperative game, admitting a NE solution. Munir et al. [29] consider uplink in HetNets, integrated with mmWave technologies, and optimize network resources while maximizing energy efficiency through a two-layer non-cooperative game. Zhong et al. [30] consider the problem of user association in HetNets. They formulate this as a multi-leader multi-follower Stackelberg game [31], where the base stations act as leaders and users act as followers, with a goal to balance the load among the base stations, while considering the backhaul bottlenecks of the base stations, and the capacity of the users' equipment.

Haddad et al. [33] propose a game theoretic framework for User Association (UA) in HetNets. The authors use the Price of Anarchy (PoA) metric, defined as the worst-case ratio between the optimal solution and any NE, as a performance indicator. PoA is also used by Caballero et al. [32]. Therein, the authors use GT to analyze network slicing, a concept in 5G networks, where the network infrastructure is "sliced" into logical networks, owned by different entities. The size of each slice is determined through a game between the owners of the slices and the infrastructure. Finally, beyond the solutions concepts centralized around NE, various other game-theoretic concepts have been utilized. Here we provide two indicative examples, connected to RA. Gorla et al. [34] use the well-known VCG mechanism (see e.g., Chapter 9 from [17]) to efficiently allocate spectrum among users in 5G networks. Sekander et al. [35] use matching theory [36] for UA in DUDe. More precisely, they present a matching game where base stations and users rank one another and provide an algorithm which converges in a stable and efficient solution, where each user is associated with at most two base stations for Uplink and Downlink.

VII. Conlusion – Future Work

Based on the above, the main challenges on RA in 5G networks can be summarized in the following: 5G network architecture is more complex than the previous cellular networks and this makes the spectrum resource allocation a challenge. In this direction the technologies presented in this paper (MIMO, DUDe, ML and Game Theory) can used to formulate the problem and present possible solutions. Energy efficiency is another challenge for RA in 5G networks. It is important to consider the trade-off between implementation of new approaches in RA (like the approached investigated in this paper) with the cost on power consumption on mobile devices. On other important issue is the scalability and the minimization of Latency of new proposed RA approaches especially when technologies like DUDe are incorporated. The industry is shifting from 4G (which enables speeds of a few megabits per second) to 5G, which promises a tenfold increase in data throughput. However, 5G is much more than simply higher bandwidth. 5G is basically a re-architecture of network infrastructure that incorporates a number of significant technologies like MU-MIMO, DUDe, ML and GT advancements and places it on a path to allow for much greater expansion. Based on the presented state of art research we to plan to propose innovative algorithm for RA in 5G networks based on MU-MIMO, DUDe, ML and GT in the context of ERA5G-Beyond project.

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