Multi Agent Team Learning in Disaggregated Virtualized Open Radio Access Networks (O-RAN)

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Abstract—As we are moving towards the new era of 5G supported verticals and their services, there is a surge in the mobile network investments and equipment deployments. The traditional monolithic mobile network radio access equipment, generally called as the base station (BS), houses radio units (RU), processors and accelerators along with proprietary software. With the advances in cloud technologies, disaggregated Radio Access Network (RAN) architectures emerged in the past decade, where Network Functions (NFs) are ripped away from specialized hardware and placed on bare metal servers. Although the concept of RAN evolution has been around for some time starting from Cloud Radio Access Networks (C-RANs), continuing with Virtual Radio Access Networks (vRANs) and most recently Open Radio Access Networks (ORANs), we are seeing commercial implementations and tests of disaggregated, virtualized and open RANs only since the beginning of 2020. One unique aspect that motivates this paper is the availability of new opportunities that arise from applying machine learning to optimize the RAN in closed-loop, i.e. without human intervention, where the complexity of disaggregation and virtualization makes well-known Self-Organized Networking (SON) solutions inadequate. In particular, Multi-agent systems (MASs) is expected to play an essential role in the control and coordination of near-real-time and non-real-time RAN Intelligent Controller (RIC). In this visionary article, we first present the state-of-the-art research in multi-agent systems and team learning, then we provide an overview of the landscape in RAN disaggregation, virtualization, as well as ORAN which emphasizes the open interfaces introduced by the O-RAN Alliance. We present a case study for ML-based disaggregation, and finally, we identify challenges and open issues to provide a roadmap for researchers.

Index Terms—Disaggregated RAN, multi-agent systems, team learning, Open RAN, virtualized RAN.

I. INTRODUCTION

The demand for mobile connectivity has been undeniably growing over the past decades, including a parallel increase in the demand for better Quality of Service (QoS). On top of that, 5G and the next generations of mobile networks will not only serve smartphone users but also businesses in self-driving cars, health care, manufacturing, gaming, marketing, Internet of Things (IoT) and many more. Almost in all generations of mobile networks, resource optimization has been a challenge, yet with 5G, despite new spectrum allocations in the mmWave band, the spectrum is still scarce with respect to increasing demand for wireless connectivity. Moreover, starting from Long-Term Evolution (LTE), the densification trend continues with 5G, at the cost of increased investments but it has become more essential due to the limited coverage of mmWave bands. The increasing complexity of mobile networks is reaching the limits of model-based optimization approaches and yielding to data-driven approaches, also called as AI-enabled networking. In this context, self-optimizing networks that use machine learning are gaining momentum [1].

In the meanwhile, an interesting nexus is emerging from AI-enabled networks and RAN disaggregation and virtualization. In 2010s, C-RAN was introduced as the first disaggregated architecture that allowed grouping Baseband Units (BBUs) into a centralized BBU pool, reducing deployment costs and improving network capacity. Other architectures have continued from the path of C-RAN, such as vRANs which adds the concept of hardware functions to be softwarized. RAN disaggregation and virtualization offers many advantages over traditional RAN solutions, such as reduced network deployment time, improved energy efficiency, enhanced mobility support and most importantly the ability to select best-of-breed solutions. Most recently, Open Radio Access Network (ORAN) concept has emerged, which uses open interfaces instead of proprietary interfaces and allows equipment from multiple vendors to be stacked together. Note that, ORAN is sometimes used interchangeably with O-RAN. O-RAN is the name of the alliance that defines the open interfaces as well as several other specifications, and ORAN refers to openness interfaces.

Within this perspective, functional splits have been an important part of the disaggregation since the decision of where to place network functions is critical. The timing of O-RAN coincides with new advances in Software Defined Networking (SDN), Network Function Virtualization (NFV), high capacity data centers, cloud and edge computing all of which have set the ideal conditions for O-RAN. Meanwhile the increased complexity and the flexible architecture of the O-RAN specifications set the perfect scene for the use of machine learning techniques.

Currently, a world-wide community named O-RAN Alliance is leading the path towards the implementation of O-RAN specifications. As of late 2020, there are a handful of implementations of O-RAN around the globe. For instance, in Japan, Rakuten has deployed distributed data centres hosting both DU and CU functions. The Spanish operator Telefonica has invested in the integration of its O-RAN solution with its multi-access edge computing (MEC) solution. On the other hand, Altiostar offers Open vRAN software solutions to several operators in the US and all over the world, such as DISH and Rakuten. In addition, some operators such as Sprint and T-Mobile in the US and Etisalat in the middle-east are in the testing phase of O-RAN in collaboration with the O-RAN software solution company Parallel Wireless. There are many
other emerging vendors, system integrators and operators who are experimenting with O-RAN, in addition to the above mentioned players in the market.

The multitude of players in O-RAN calls for machine learning techniques that involve multiple agents. In recent years, MASs have been used to address complex problems in robotics and other self-driving systems therefore they emerge as promising alternatives for the self-driving (or self-optimizing) capability of O-RAN. To the best of our knowledge, this paper is the first to elaborate on multi-agent learning and its use in O-RAN. Fig. 1 illustrates AI-enabled NFs (AIeNFs) being deployed at RU/DU/CU and organized as teams by the RIC of O-RAN. With this, RIC can work as a self-optimization engine carrying the 3GPP Self-Organized Networks (SON) concept to the next level of network automation.

In the literature, there are several comprehensive surveys on MAS. For instance, in [2], the authors provide an extensive discussion of all aspects of MASs, starting from definitions, features, applications, challenges, and communications to evaluation. Meanwhile, [3] covers recent relevant cooperative Multiagent Deep Reinforcement Learning (MA Deep-RL) developments and applications in the real world. Unlike previous surveys on MAS, this paper focuses on the application of multi-agent learning in the modern RAN environment. We first begin with an introduction on MAS and learning in MAS, and then continue with giving background on recent advances in RAN by using a case study. Finally, we provide a detailed discussion on the challenges of multi-agent learning in disaggregated, virtualized, open RANs and identify open issues in the field.

II. BACKGROUND ON MULTI-AGENT SYSTEMS

A MAS is a group of autonomous and intelligent agents that act in an environment in order to accomplish a common goal or individual goals. There can be several types of MAS, such as homogeneous/heterogeneous, cooperative/collaborative/competitive and communicating/non-communicating.

The most common taxonomy found in the literature classifies MASs in two main groups: homogeneous and heterogeneous MASs. Then, depending on how the agents communicate, they are classified in communicating and non-communicating. The taxonomy of MAS is given in Fig. 2.

**Homogeneous**: In this architecture, the multi-agent system consists of agents with a similar internal architecture, which means that all agents have the same local goals, capabilities, actions, and inference models. In homogeneous architecture, the main difference among agents is based on the place where their actions are applied over the environment.

**Heterogeneous**: In this structure, agents may have different goals, capabilities, actions, and inference models.

**Communicating/non-communicating**: A group of agents can be designed to communicate with each other or not. When there is no communication, agents act independently, and they don’t use feedback from other agents however they may be working in the same environment hence receive indirect feedback on the actions of the other agents.

In a MAS, agents can be cooperative, competitive, or mixed. In general, if they are cooperative, agents communicate with each other. For the competitive case, they may or may not communicate, or they may share partial information.

**Cooperative**: In a cooperative setting, the agents need to take collaborative actions to achieve a shared goal, or in other words, agents must jointly optimize a single reward signal. To achieve a goal, agents communicate in this case.

**Competitive**: In a competitive setting, each agent tries to maximize one’s own reward under the worst-case assumption meanwhile the other agents always try to minimize their own reward.

It is also possible to have teams with mixed behavior agents where some are cooperative and some are competitive.

Although many machine learning techniques have been considered for MAS, team learning is of particular interest.
A. Team Learning in MAS

In team learning, teams of agents are usually assumed to be distributed, cooperative, and completely share information on observations. However, it is also possible to consider a mixed behavior MAS with partial observability (i.e. partial information sharing).

Team learning has been studied and applied for a wide range of applications. From multi-robot teams (e.g., Robot soccer), multi-player game-plays (e.g., Dota, StarCraft), predator-prey pursuit and capture problems, to search and rescue missions, team learning has been used to address complex problems where collaboration or competition among agents is present.

Recent applications on team learning in the scope of multi-robot teams have been addressed with reinforcement and deep learning techniques. For instance, in [4] the authors propose a novel approach for coordination among a team of robots using their relative perspective-based image. The goal is to deal with resource competition and static and dynamic obstacle avoidance problems among the team members.

Search and rescue mission is another application type where team learning has been of great interest due to its practicality in hostile environments. In [5], the authors study the behavior of heterogeneous robots in damaged structures, where exploration of such structures for locating the trapped humans is the prime goal. A framework on how team maintenance and task management among teams is described in this work. Dynamic aggregation and switching of robots and their roles among teams are the main contributions of the proposed methodology.

Finally, an interesting work related to team learning in urban network traffic congestion is presented in [6]. The authors proposed a Dynamic Traffic Assignment (DTA) algorithm based on collaborative decentralized heterogeneous reinforcement learning approach to mitigate the effects of the randomness of urban traffic scenarios. In this setup, two agent groups are defined as advisers and deciders. The deciders assign the flows of traffic network meanwhile the advisers communicate support information exclusively with the deciders.

In the next section, we first provide background on RAN disaggregation and virtualization, and then overview MAS applications in this domain.

III. BACKGROUND ON DISAGGREGATED, VIRTUALIZED AND OPEN RAN

Earlier RAN solutions offered an architecture where BBUs and RUs were co-located. This brought limitations in terms of not being able to pool BBU resources. Therefore the next phase of RAN architectures considered BBU resources that are pooled close to the radios but not co-located, where geographical proximity is necessary due to latency limitations. The pool of BBUs is called Distributed Unit (DU), and the radios constitute the Radio Unit (RU). Within O-RAN specifications, another level of processors is also defined which is called as Central Unit (CU). The link between RU and DU is the fronthaul, and the link between DU and CU is referred as the midhaul.

The most appealing reason behind disaggregation is to reduce costs and bring more versatility to the technological market. An earlier version of RAN disaggregation is seen in C-RAN where some hardware functions are implemented as software functions and BBU functionality is collected at the centralized cloud. C-RAN offers improvements in network capacity, handling cooperative processing, mobility, coverage, energy-efficient network operation and reduced deployment costs [7].

On the evolution path of RAN architecture, the most recent development comes with O-RAN, in which interfaces between RU-DU and DU-CU are based on open specifications and not proprietary unlike previous RAN implementations, meaning inter-operability between vendor products and selection
of best-of-breed technology by Mobile Network Operators (MNOs) will be possible. In addition, O-RAN embraces intelligence in every layer of its architecture and aims to leverage new machine learning-based technologies. In 2018, the O-RAN Alliance is created with the objective of evolving the RAN to a more open and smarter network. A recent survey on open virtualized networks [8], gives a comprehensive overview of the state-of-the-art in modern RANs.

In the next section, we present functional splits and slicing which are important concepts to understand the insights of disaggregation in RAN.

A. Disaggregation, functional splits and slicing in RAN

Disaggregation, functional splits and slicing are three closely related concepts. As mentioned before, C-RAN architecture allows an operator to decide the location of each function module either in the centralized BBU pool or in the RU. The separation of network functions between these two entities is referred to as a functional split. The location of such modules defined by each possible split has been of great interest given the fact that, by moving them either to the RU or the centralized BBU pool, it is possible to balance tradeoff between the fronthaul traffic and the latency.

Significant amount of research has been done on functional splits. In [9], the authors analyze and compare functional split options in terms of delay and jitter. The analysis is performed using an experimental testbed based on Software Defined Radios (SDRs) and Open Air Interface (OAI). The implemented splits are option 7 (intra-PHY), option 6 (MAC-PHY), and option 2 (PDCP-RLC). For this specific evaluation, the MAC-PHY split presented the best performance in terms of delay and jitter.

Meanwhile, in [10], the authors present a comprehensive survey by providing a comparison between the possible splits in three different categories: references from theoretical surveys, references from simulations and references from practical experiments are studied. Starting from the option with the most simple DU (split 8) going towards the most complex DU which corresponds to the split 1 (RRC-PDCP), each split is analysed in terms of advantages, disadvantages and respective use cases.

Furthermore optimum allocation of the functional splits has been studied in [11]. The authors focus on power and deployment cost minimization while supporting splits on a user basis. Thus, a user-centric functional split approach is utilized and a particle swarm optimization technique is proposed to minimize the bandwidth constraints given by the selection of different splits.

Finally, network slicing in RAN is necessary to support the requirements of different user types that need to be dynamically orchestrated in 5G [12]. By using logical slices, one physical network is able to tackle various traffic types at the same time. As mentioned earlier, a close relationship exists between splits and slices. For instance, different functional splits can be assigned for different slices in order to obtain the best resource utilization and performance. Recently machine learning techniques have been used in many studies for the automation of network slicing.

In the next section, we present a brief overview of applications of MASs in disaggregated networks as the first step of multi-agent learning in new RAN architectures.

B. MAS applications in disaggregated networks

Most of the recent MAS applications are related to dynamic resource allocation, scheduling, beam selection and task offloading. Some recent works are summarized below.

MASs in resource scheduling multi-RAT access

Although multi-RAT access is not new in O-RAN, most of the NFs of RAN will have to work in a disaggregated environment and over multiple RATs. In [13], the authors address this issue in a traditional RAN by proposing a Smart Aggregated RAT Access (SARA) strategy based on multi-agent reinforcement learning to maximize the average system throughput while satisfying the UEs’ QoS preferences. The proposed algorithm consists of a model-free multi-agent reinforcement learning to solve a Semi-Markov Decision Process (SMDP) based on Hierarchical Decision Framework (HDF).

MASs in Dynamic Beam Selection and fog RAN (F-RAN)

In [14], the authors present a novel fog RAN (F-RAN) testbed to tackle some of the issues of C-RAN. In this architecture, access points and user equipment present some computing capabilities that reduce fronthaul load and comply with low-latency applications. An evaluation of intelligent beam pair selection using reinforcement learning, in particular, actor-critic learning has been considered.

Most of the prior work that focuses on multi-agent learning considers multiple uncoordinated agents working within the same environment, driven by the same rewards or goals. However, when multiple agents interact with the environment independently - thus, changing the environment of each other-, or when they have different goals, the problem cannot be simplified to deploying independent agents. The least to say, this approach would not lead to optimal results. Whereas teams of agents working together to optimize RAN performance jointly would yield to better results. As a first step towards team learning within O-RAN, we study the bandwidth requirements for intelligence placement.

IV. A CASE STUDY ON TEAM AGENT PLACEMENT AND O-RAN FRONTHAUL RANGE

As the O-RAN architecture attempts to embed intelligence into multiple layers and functions, it is natural to consider that intelligence will be split. Accordingly, this provides the possibility of invoking AI agents at different layers to either access higher processing power to optimize more complex problems (at the CU) or apply real-time actions for low latency services (at the DU). As it is shown in Fig.3, each O-RAN component needs to abide by a certain delay bound that is tolerable within its control loop. This is closely related to the fronthaul/midhaul bandwidth and the range.

To determine the maximum fronthaul/midhaul range (referred as XHaul range from hereon), maximum tolerable delay at each layer needs to be considered. The overall delay of the closed-loop control can be represented by the round
trip time (RTT) of AI feedback, which includes processing, transmission and propagation delay over the XHaul. The maximum allowable range of the XHaul is proportional to the propagation delay of the physical link. As shown in Table I, each functional split option has its own delay budget and bandwidth requirement. Hence, the minimum allowed one-way latency presented in the table becomes the limiting factor for the maximum allowable range. Since machine learning algorithms will be using the same feedback of these splits, it is important to consider these latency budgets and consider ranges accordingly.

The type of medium used for XHaul is also a primary factor that affects the range. For instance, the propagation delay in fiber optic is around $5 \mu s/km$. This value can be reduced to $4 \mu s/km$ and $3.34 \mu s/km$ if coaxial cables and mmWave technologies are employed, respectively. At the same time, the propagation delay in Ethernet is $50 \mu s/km$, which is much higher with respect to fiber optic, mmWave, and coaxial cables. As a case study, we focus on midhaul and in Fig. 4, we provide the maximum range for several technologies under varying packet sizes. It is important to note that, as the feedback of AI techniques increase (i.e. larger packets), the DU and CU needs be located closer. Hence, while designing team learning algorithms or other MAS techniques, the amount of communication between agents becomes a critical issue. In addition, although implementing AI agents at upper layers of O-RAN (for instance, CU) can provide broader perspective of intelligence due to the accessibility of other agents’ observations and access to more processing power (which allows optimizing more complex problems), the location of agents and the amount of data that needs to be transmitted between CU and DU can negatively impact the network performance. Therefore, when invoking teams of agents at different layers of O-RAN, bandwidth and latency requirements of the XHaul needs to be taken into consideration.

In the next section, we further elaborate on the challenges

![Fig. 3: O-RAN closed-loop latency requirements and the intelligence at different layers of O-RAN.](image)

| Split Option | Minimum required bandwidth (Gbps) | Minimum allowed one-way latency (ms) | midhaul range (km) |
|--------------|----------------------------------|--------------------------------------|--------------------|
| Option 1     | 3                                 | 10                                   | 400                |
| Option 2     | 3                                 | 1                                    | 40                 |
| Option 3     | 3                                 | 1.5                                  | 60                 |
| Option 4     | 3                                 | 100                                   | <1                 |
| Option 5     | 3                                 | 100                                   | <1                 |
| Option 6     | 4.1                               | 250                                   | 2.7                |
| Option 7a    | 10.1                              | 250                                   | 7                  |
| Option 7b    | 37.8                              | 250                                   | 9.2                |
| Option 7c    | 10.1                              | 250                                   | 7                  |
| Option 8     | 157.3                             | 250                                   | 10                 |

TABLE I: Bandwidth and latency requirements of functional splits [15].
and the opportunities of multi agent learning in O-RAN.

Fig. 4: Maximum XHaul range under different technologies and varying packet size.

V. OPEN ISSUES AND FUTURE DIRECTIONS FOR MULTI AGENT LEARNING IN O-RAN

Despite many potential benefits of machine learning in the disaggregated, virtualized, open RANs, it is hard to deny the numerous challenges that need to be addressed before AI or ML can take over RAN functions. In this section, we identify the challenges, open issues and opportunities in multi-agent learning for the future RAN architectures. Note that, some challenges are already fundamental issues in learning in the MAS environment while others are only specific to new RAN architectures.

- **Convergence time:** Just like any other machine learning technique, team learning techniques designed for the RAN should converge and should converge fast. In case when fast convergence is not possible, fast boot strapping techniques or offline training needs to be considered.
- **Scalability:** Dimensionality issues have been a recurrent issue when the number of agents (so as the states and actions) in a MAS tends to increase. As more NFs become intelligent agents in RANs, the scalability of learning, inter-agent communication and environment feedback needs to be taken into consideration.
- **Lack of full observability:** As intelligent NFs act in their own environment, they will be simultaneously modifying the environment of other agents. Therefore, to take an optimal action, each agent will need to predict and estimate other agents’ actions. Hence, decisions need to be made based on the agents’ partial observations, which can result in a sub-optimal solution.
- **Information sharing:** It is essential to decide how much of the available local information should be shared among agents for enhancing the modeling of an environment. As addressed in the previous section, this should be jointly considered with fronthaul and midhaul technologies and the functional split decisions.
- **Selecting the optimal team size:** Choosing the optimal team size can affect learning and system performance.

Although a larger team can provide wider visibility over the environment and access more relevant information, the incorporation and learning experience of each agent can be affected. Meanwhile, one can obtain faster learning within a smaller team size, but due to the limited system view, a sub-optimal performance may be achieved.

- **Goal selection:** In a RAN environment, the agents may reach some decisions where the network performance is degraded, even though the individual agents intended to maximize the performance. The goal of team learning should be minimizing conflicts and focusing on overall performance enhancement.
- **Impact of delayed feedback and jitter:** Most MAS studies consider that the feedback from the environment is immediate, and if agents are communicating, their feedback is instant. However, in disaggregated RANs, feedback can be intentionally or unintentionally delayed. Delayed feedback may cause agents to interact with diverged versions of the environment, and lead to degraded RAN performance.
- **Security and trust:** Most MAS rely on the truthfulness of information shared among agents. Although there are studies on uncertainty or partial observability, intentional wrong reporting and adversarial behavior should also be considered.

VI. CONCLUSION

In this paper, we motivate the use of multi-agent team learning as a way of embedding intelligence in disaggregated, virtualized, open RANs. We first give an overview of MAS and team learning, and then we give a short summary of RAN evolution from C-RAN to vRAN to O-RAN. We present a case study on the requirements of XHaul range when intelligence is embedded at different layers of O-RAN. Finally, we provide a detailed discussion on challenges, open issues and future directions.

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