Thesis Proposal: Machine Learning Framework for Radio Access Network Slicing with UAV Base Stations

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Summary of the Proposal

Network slicing is one of the key enablers of 5G. Its main idea is to provide a service-oriented architecture, where the physical network is partitioned into virtual networks to provide support for a wide variety of services. A global effort has been made to define standard typologies of services, or slices, that are going to prevail in 5G networks:

- enhanced Mobile Broadband (eMBB), characterized by high data rates requirements;
- massive Machine Type Communications (mMTC), where a massive deployment of devices is characterized by small payload transmissions and sporadic activity;
- Ultra Reliable Low Latency Communications (URLLC), defined by services requiring ultra-low latency and high reliability.

The coexistence of these heterogeneous services requires an efficient resource slicing framework, where network resources have to be allocated according to the diversity and dynamicity of the slices' requirements. In this regard, Machine Learning (ML) approaches have proved to be able at solving non-deterministic problems, making real-time decisions to maximize the network performance over time. However, the design of a ML framework in communication networks is not straightforward, given the strict constraints in terms of Quality of Service (QoS) and Quality of Experience (QoE).

At the same time, several works have also proved that placement and trajectory design in wireless network can drastically help in taking full advantage of the system. Unmanned Aerial Vehicles (UAVs) are the perfect choice to deploy highly dynamic nodes. They are drawing a lot of attention, especially in 5G New Radio standards, for their ability to replace or extend the capabilities of existing ground radio infrastructures.

The objective of this work lies in merging a resource slicing approach and a proper spacial placement of the network's nodes, in order to help meeting the stringent requirements of resource slicing. The consideration of UAVs as base stations brings more complexity to the resource slicing environment. They have battery constraints, different channel characteristics and are subject to strict international regulations. However, a large variety of recent works stressed on the importance of the role that UAVs will cover in the next generation wireless communications, matched by several benefits that they can bring to wireless network coverage and capacity enhancement.

This project will thus aim at finding a proper methodology to propose a ML framework that is able to cope with these dynamic and constrained environments, by handling both resource allocation for network slices and a proper placement of the base stations.

Background

The key components for network slicing can be classified into: **Radio Access Network (RAN) Slicing**, **Core Network Slicing**, and **Management and Network Orchestration**. RAN slicing mainly consists in the allocation of radio resources to User Equipments (UEs) belonging to different slices, consistently with their own requirements in terms of data rate, latency, and/or reliability. To do that, RAN functionalities are split into a set of Virtual Network Fuctions (VNF), which allow the slices to be physically or logically isolated, and hence, to flexibly adapt the RAN resources.

Core Slicing is the most mature concept in Network Slicing, as it is already present in 3GPP standards under the name of "DECOR". Core Network slices are realized through VNFs, such as network registration, mobility management or user plane forwarding. Current research in core slicing is mainly oriented in VNFs management for their heterogeneous resource requirements.

MANO is the entity that manages the end-to-end nature of slices, spanning from the RAN to the Core, as well as their life cycle management to ensure compliance with the Service Level Agreement (SLA) required by each slice.

While the core network slicing has been deeply investigated and standardized [3], lack of research is present in the RAN part. More specifically, one of the main challenges faced in this field consists in the dynamic radio resource allocation to slices over time. In fact, the variable traffic demand each slice is subjected to is not suited for a static resource allocation, which leads to a waste of resources and violations of SLAs. Suitable algorithms are needed in order to dynamically adapt the heterogeneous demand coming from the slices to a proper allocation of resources.

This heterogeneous nature of slice requirements, together with the large amount of data that flow in the network, make the majority of existing approaches unfeasible to these environments [7]. Machine Learning (ML) methods, on the other hand, are gaining a lot of interest in the research and development of communication networks.

Existing ML approaches for RAN slicing are mainly developed to solve two classes of problems: **Slice Admission Control** and **Inter-Slice Resource Allocation**. In the first scenario, the Slice Orchestrator (SO) has to perform a yes/no decision upon slice creation requests from Mobile Network Operators (MNO). The SO should take this decision considering the SLA of the new potential slice, the available resources in the network, and the monetary value that comes after accepting the request. The second scenario involves a dynamic allocation of resources between already existing slices. Typically, the goal is to allocate portion of bandwidth to the slices over "allocation time windows". Within each allocation window, the internal scheduler executes a user-scheduling algorithm (Round-Robin, Proportional Fair, etc...), allocating physical resource blocks (PRBs) according to the portion of bandwidth that was previously allocated to the slice by the SO.

As best of our knowledge, three main groups of ML approaches have been proposed to deal with these scenarios:

1. Reinforcement Learning (RL) for Slice Admission Control, where an RL agent has to take the yes/no decision regarding the creation of a new slice according to the current state of the network (e.g., SLAs, available resources, existing slices) [4];

2. Slice Traffic Demand Prediction with Artificial Neural Networks, where supervised ML is exploited to analyse temporal correlations among the observed traffic patterns and to forecast future slices demands [1];

3. RL-based Dynamic Inter-Slice Resource Allocation, where an RL agent directly assigns radio resources to slices at each allocation window, according to the network state observation [5].

As mentioned in the introduction and demonstrated by Miranda et al. [6], network performance is strongly affected by the position and mobility of the base stations/routers. Their placement can significantly improve or deteriorate quality of service indicators, such as end-to-end delay, jitter and throughput. In this project, we want to exploit this characteristic in order to efficiently place the base stations in the network while running an inter-slice resource allocation, in order to meet the SLAs of all the slices. Base station placement problems are usually considered when dealing with UAVs as base stations, which have the ability to rapidly deploy a network and to provide support to extend/replace the existing communication infrastructures. Bithas et al. [2] claim how the adoption of UAVs is going to become an integral part of the next generation wireless communications, and how position related aspects are of critical importance for aerial wireless network coverage and capacity.

Objectives and Methodology

As presented in the background section, RAN slicing and Inter-Slice Resource Allocation are witnessing an increasing interest in the communication research community. The preliminary literature review that has been carried out, has shown large interest towards ML applications in this context. However, the lack of benchmark for RAN slicing algorithms makes the comparison of these approaches not solid.

The first objective of this project is to define a baseline scenario where to test a large set of already existing algorithms, in order to have a preliminary benchmark of different approaches in the same environment. To achieve this goal, an extensive literature review regarding RAN slicing algorithms will be carried out, together with the implementation of a simulated environment where to implement and test them. The metrics for these comparisons are going to be decided and standardized. They must contain information regarding the algorithms' space and time complexity, the SLAs required from the slices, and the scalability of the approaches with respect to the number of users, slices, and/or base stations deployed.

The second objective consists in the proposal of an optimization resource slicing and UAV placement problem that maximizes the SLA satisfaction ratio of the existing slices. Due to the dynamic nature of the environment, an end-to-end ML framework for Inter-Slice Resource Allocation will be implemented in the same simulated environment obtained as output of the first project objective. The implemented ML method will be based on RL, considered the sensational results that this approach has achieved in distinct research fields (board games, collaborative tasks, performance enhancement in communication systems). Many state-of-the-art RL algorithms can be used and adapted to different scenarios. This second objective will be focused on the study of these algorithms, their application to RAN slicing environment, and an intensive tuning of the chosen algorithm's hyper-parameters. The focus will be on Deep Reinforcement Learning algorithms, given their outstanding performance and innovation brought in the past five-six years. They merge traditional RL and function approximators (e.g., neural networks) in order to speed up the convergence time, to reduce the space complexity, and to deal with large state-space problems.

The third and last goal is a long-term achievement. In the aforementioned cases, we always considered a centralized entity that is able to take decisions for each agent of the system. In order to reduce the perceived computational complexity at the SO, an effort should be made to distribute the learning process over different participants in the environment. The idea is that each UAV-BS is only able to receive a partial observation of the environment, and it allocates resources/move accordingly. These scenarios are typically modeled as Partial Observable Markov Decision Processes and can potentially be solved through RL. Multi-Agent Reinforcement Learning (MARL) in communication networks, in particular, is considered as a promising technology to reduce the network overload and improve its performance. A more solid theoretical background will be needed in order to justify these statements, together with a more in-depth study of distributed algorithms in baseline environments deployed in the previous two objectives.

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