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A beyond simulation deep reinforcement learning agent for network slicing in autonomous IoT systems

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1 Introduction

The rapid increase in the number of IoT services mirrors the growth in IoT devices, necessitating a shift in IoT systems' Quality of Service (QoS) paradigm. This shift moves away from a one-size-fits-all QoS approach to a tailored QoS model, where each IoT service is provided with precisely the QoS it requires. In 5G networks, Network Slicing (NS) enables this customization by creating bespoke network slices. Coupled with trends such as Zero-Touch Networks, autonomous IoT systems, and Self-Driving Networks, NS must dynamically create, manage, and terminate slices on demand. In our study [1], we address this need by proposing an autonomous DRL-based slice placement agent.

2 Network slicing concept

The concept of Network Slicing, introduced by the NGMN (Next Generation Mobile Network), is closely associated with 5G networks. As illustrated in Figure 1, its operation relies on two key components: a physical infrastructure and slice requests. Computing nodes have limited resources such as CPU, RAM, and storage, which must be shared among the Virtual Network Functions (VNFs) of all requests. Similarly, the limited bandwidth of physical links must be efficiently utilized for virtual link chaining, as depicted in the figure. This work focuses on optimizing network slicing in terms of the acceptance ratio, i.e., the number of slices successfully deployed.

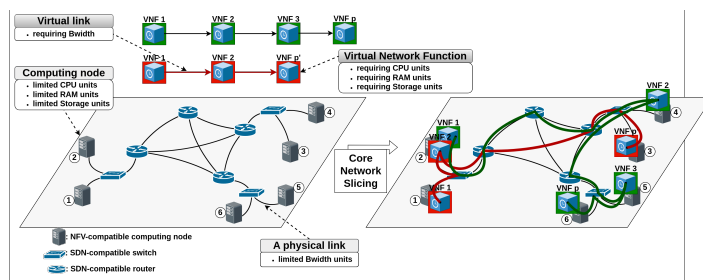


FIG. 1: Network Slicing illustration

3 Oneshot Deep Reinforcement Learning agent

Before our work, DRL-based Network Slicing (NS) approaches sequentially processed VNFs, predicting placements one at a time. However, this method conflicts with ETSI OS MANO [3],

which requires all VNF placement decisions to be submitted simultaneously. Our algorithm addresses this by using micro-agents to determine all placements in a single DRL iteration (Oneshot). Each micro-agent trusts prior decisions, and if errors occur, the master agent learns from them, updates the policy, and redistributes it for better future placements, aligning with DRL’s long-term optimization approach.

4 Simulation results

Figure 2 presents some simulation results using ns3-gym simulator comparing slice placement acceptance ratio under load balancing constraints on an infrastructure similar to the one in Figure 1 (inspired from the infrastructure in [2]). Our Oneshot DRL agent is evaluated against six alternatives: (1) Sequential DRL, placing VNFs one by one with rewards only for the last, (2) Integer Linear Programming (ILP), achieving up to 100% placement but requiring all requests in advance and exhibiting all-or-nothing behavior, (3) GAVA, a genetic algorithm, (4) Random Performer, placing VNFs randomly, (5) Max Performer, placing VNFs on nodes with the most resources, and (6) First-Fit, placing VNFs on the first available node. Results show that Oneshot DRL performs comparably to ILP when resources are abundant and outperforms it under resource constraints, successfully placing around 50% of slices compared to ILP’s 0%.

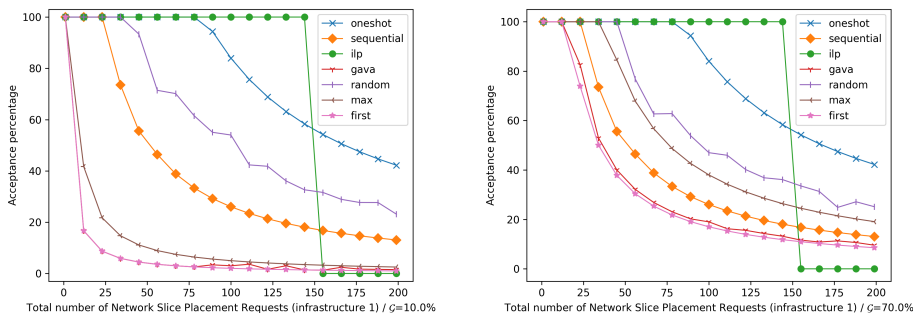


FIG. 2: Some simulation results from [1] comparing acceptance ratio under load balancing constraints

5 Conclusions et perspectives

In article [1], we proposed a DRL algorithm for autonomous network slicing, designed for seamless transition from simulation to real-world deployment. Future work will focus on deploying the algorithm on Grid5000 and later on a 5G platform. Additionally, a distributed version will be developed to address multi-domain scenarios.

References

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