Availability-Aware Network Slicing and Dynamic Function Placement in Virtualized RANs with Reinforcement Learning

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Abstract

As 5G virtualized Radio Access Networks (vRANs) continue to evolve, optimizing the placement of Virtualized Network Functions (VNFs) becomes crucial for enhancing network performance and meeting diverse service requirements. This work presents a Reinforcement Learning (RL) based approach to dynamically address VNF placement challenges in 5G vRANs. Many Integer Linear Programming (ILP) based approaches in the literature optimize VNF placement based on latency, and resource constraints. However, their static nature limits adaptability and scalability in real time. To address these challenges, our RL-based approach models the VNF placement problem as a Markov Decision Process (MDP), enabling dynamic decision-making to optimize VNF placement and network slicing. Evaluations on realistic 5G topologies show that the RL-based solution outperforms ILP regarding request acceptance, centralization, and computational efficiency.

Introduction

As 5G networks evolve, optimizing virtualized network function (VNF) placement in vRANs is crucial to meet the diverse demands of services like URLLC, eMBB, and mMTC. Existing solutions, such as SliAvailRAN[1], use ILP to solve this problem but struggle with real-time adaptation and scalability. In this paper, we propose an RL-based extension to SliAvailRAN[1] that dynamically adjusts VNF placement based on network conditions. By modeling the problem as an MDP, our RL approach adapts to dynamic requests and resource availability, improving performance over static ILP methods in large-scale vRAN environments.

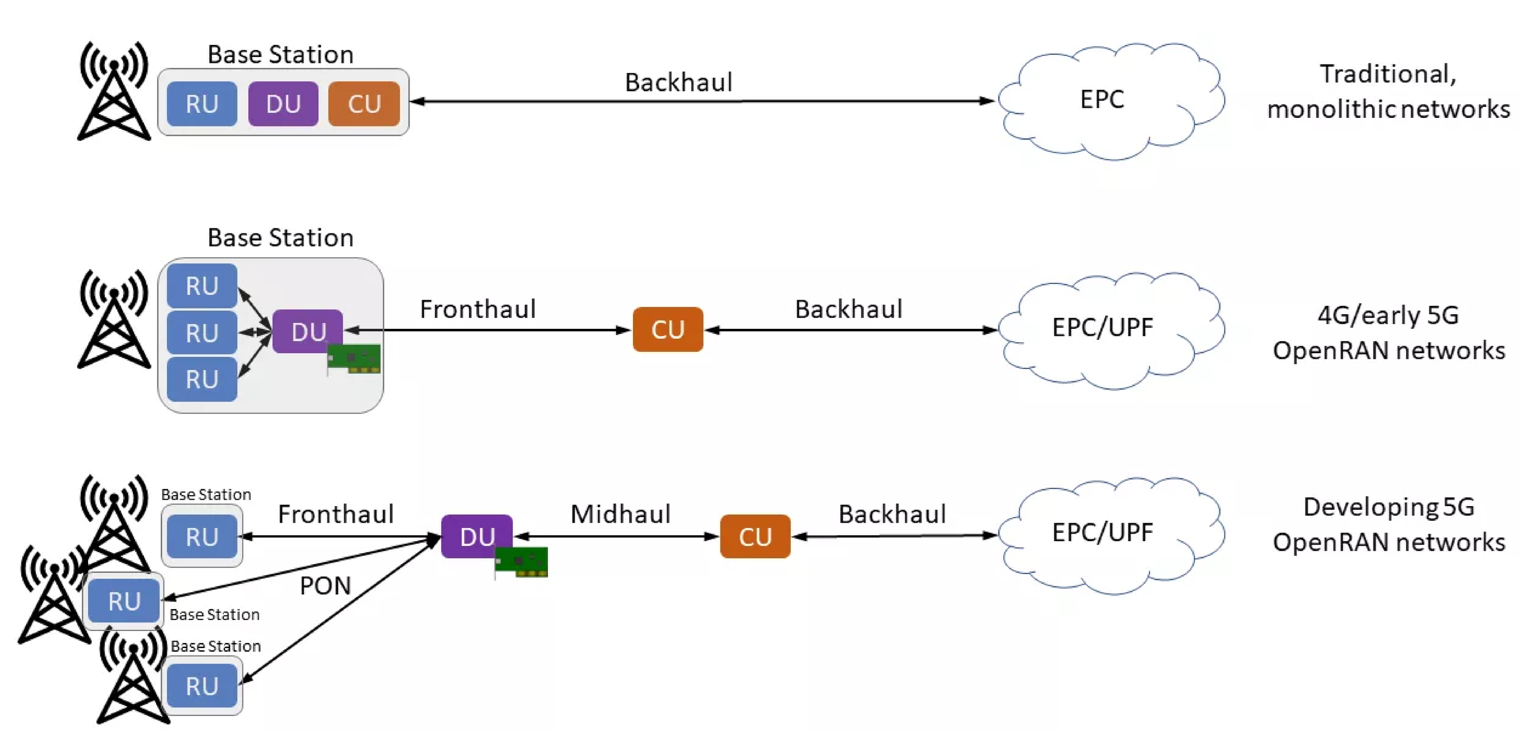

Figure 1. Virtualized Radio Access Network(vRAN)

Proposed Work

Goal : SliAvailRAN[1] seeks to maximize the service provider's profit by balancing network revenue with the costs of designing the virtualized Radio Access Network (vRAN).

- **Cost Components:**
  - **Revenue from Requests:** Revenue generated depends on the accepted slice type (e.g., URLLC, eMBB, mMTC).
  - **Node Activation Cost:** Incurred when deploying functions on nodes.
  - **Wavelength Activation Cost:** Cost of activating wavelengths on links.
  - **VNF Instantiation Cost:** Varies by node type—Central Units (CUs) are cheaper to instantiate due to enhanced resource pooling compared to Distributed Units (DUs) and Radio Units

Highlight of your Proposed Work

We extend the SliAvailRAN[1] framework by creating a custom environment and applying Proximal Policy Optimization (PPO) to optimize the placement of virtualized network functions (VNFs) in 5G virtualized RANs. PPO, a reinforcement learning algorithm, is used to dynamically adapt to real-time network conditions, outperforming static optimization methods like ILP.

- **Custom Environment:** Simulates vRAN components such as CPU capacity, bandwidth, latency, and wavelength availability.
  - **State Space:** Represents real-time network conditions, including CPU, bandwidth, and latency.
  - **Action Space:** Involves selecting VNF placements, wavelengths, and disjoint paths from the RU to the Core Network.
  - **Reward Function:** Encourages request acceptance, centralization, and resource efficiency while penalizing excessive resource use.

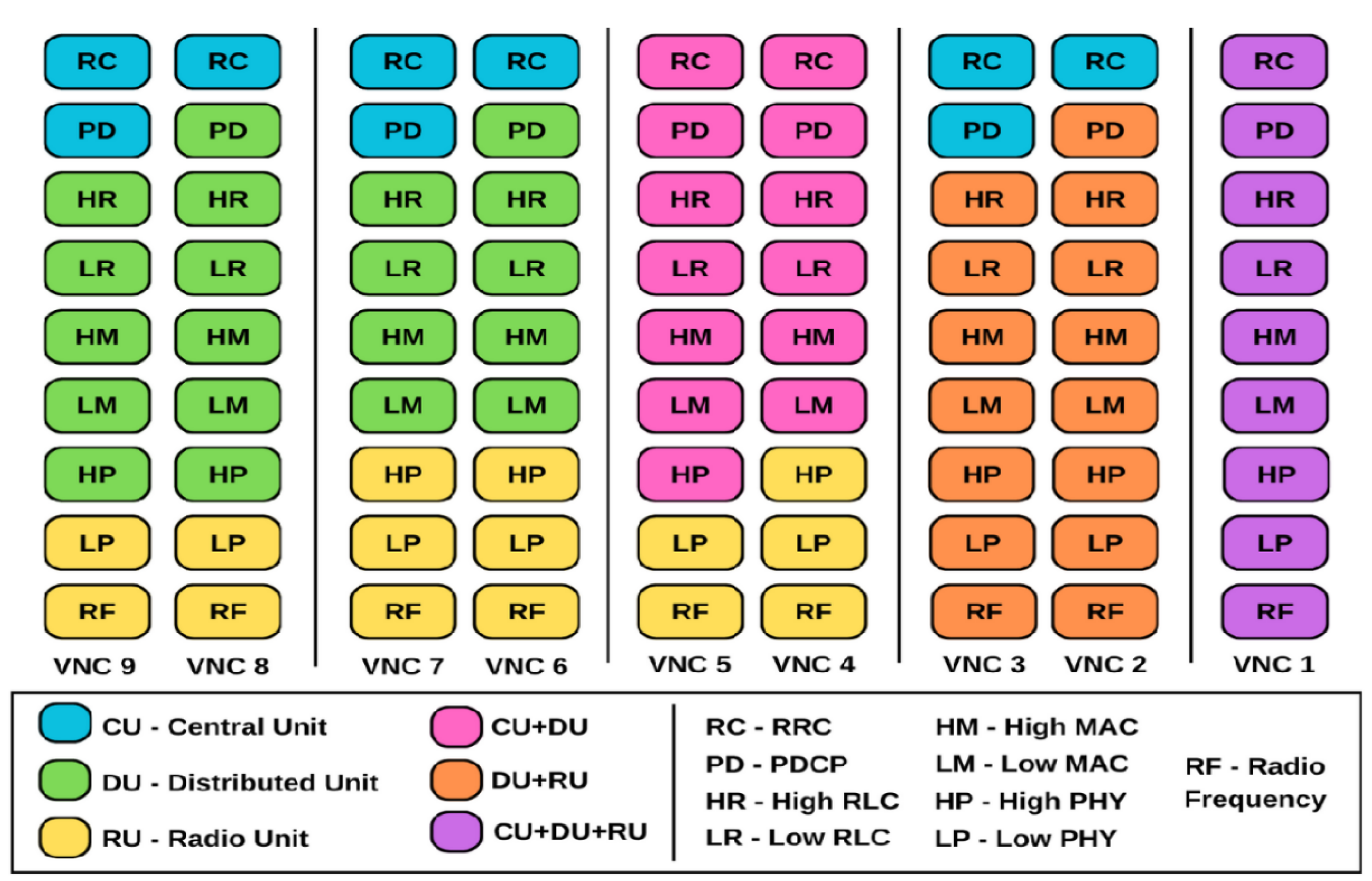

Figure 2. Considered VNCs and corresponding placements of radio network functions on RU, DU, and CU nodes.

- **Constraints:**
  - **Primary path constraint:** Each request must have exactly one primary path if accepted.
  - **Backup Path Constraints:** At least a specified number of backup paths must be available for each request.
  - **One-to-One Mapping:** Each accepted request should be linked to exactly one Virtual Network Configuration (VNC).
  - **Disjoint Node Selection:** Backup nodes for each request must be disjoint to ensure availability.
  - **Path Disjointness:** Selected paths for a request cannot share any CU or DU nodes.
  - **Wavelength Continuity Constraint :** This constraint ensures that if a wavelength is used on path for VNC, then the same wavelength must be assigned to all links on that path.
  - **Unique Wavelength Assignment Constraint :** This constraint ensures that a wavelength is assigned to at most one path passing through link
  - **Processing Capacity:** The total processing load on a node must not exceed its capacity.
  - **Link Capacity:** Total traffic on a link must be within its capacity limits.
  - **Latency Constraints:** Selected paths must meet latency budget requirements and VNC configuration limits.
  - **Activation Constraints:** A node is activated if at least one path passing through it is selected by a request.

Results

We implement our RL framework in Python using OpenAIGym. We use two realistic sets of topologies, T1 and T2 adopted from[2] for evaluating our solution. Both these topologies have two types of variants – Low Capacity (LC) and High Capacity (HC), the latter having higher link and node capacities. T1 has only one configuration with 51 nodes (LC and HC), while T2 has different configurations with varying numbers of nodes: 8, 16, 32, 64, 128 for LC and 128 for HC. T1 is representative of current RAN deployments per the 5G crosshaul project, while T2 is derived from the futuristic RAN aligned with the PASSION project[2]. The figure below demonstrate the training process for the RL framework on a representative Low capacity T2 topology with 8 nodes. Further results and analysis is currently a Work-in-progress (WIP).

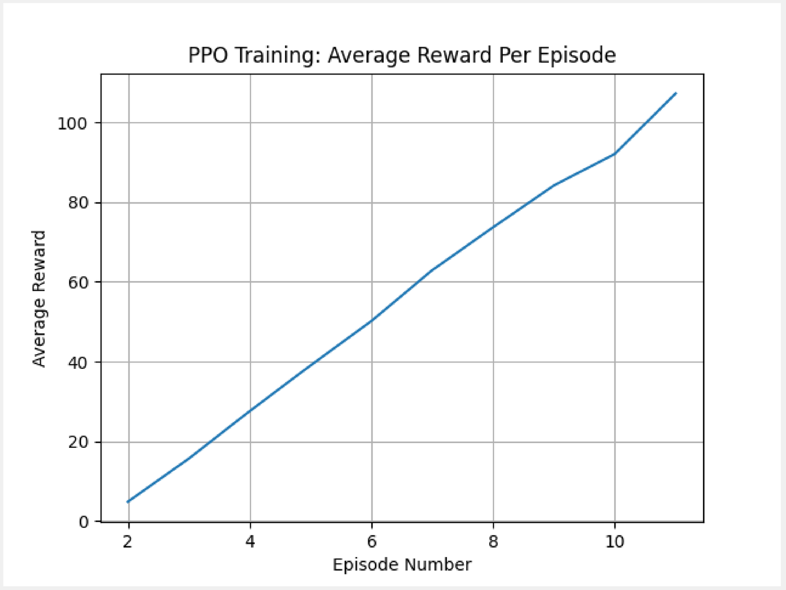

Figure 3. Average reward vs episode number

Conclusion & Future Works

In this work, we have successfully extended the SliAvailRAN[1] framework by incorporating a custom environment and applying Proximal Policy Optimization (PPO) for the dynamic optimization of virtualized network function (VNF) placement in 5G virtualized Radio Access Networks (vRANs).

The RL-based approach significantly improves request acceptance rates, resource efficiency, and centralization compared to static ILP methods, showcasing the adaptability and scalability of reinforcement learning in real-time network environments.

Currently, we process one request at a time for simplicity. Future work will explore multi-agent reinforcement learning to handle multiple simultaneous requests, enabling more efficient resource allocation and improved performance in real-world 5G networks.

Lastly, investigating the potential of other RL algorithms, such as Deep Q-Learning and Actor-Critic methods, could yield further insights into optimizing VNF placement in vRANs.

References

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