

Reinforcement Learning based resource scheduling for network slicing in vehicular networks

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Abstract—The number of mobile devices is increasing at an unprecedented rate which also increases the traffic demands. Given the limited network resources, it is natural to slice the physical network into several logical virtual networks to fulfill the service demands. The network slices providing different services on demand have certain QoS requirements which need to be fulfilled in order to provide smooth service to users in a mobile network. Specifically, in a vehicular environment, the high dynamicity calls for real-time management and scheduling of resources. In order to utilize the limited network resources efficiently while honoring the QoS requirement of each slice, it is needed to schedule the resources in real-time based on the service demands. The proposed scheme provides a reinforcement learning-based solution to schedule the resources of a base station for different slices in the vehicular environment for various on-demand services. On the basis of required and available resources, as well as the priority of service, the base station schedules its resources among different slices in real-time.

Index Terms—Reinforcement Learning (RL), Network Slicing, Resource Scheduling, Vehicular Networks

I. INTRODUCTION

With the proliferation of mobile devices, the demand for mobile data traffic is also increasing unprecedentedly. Mobile network operators are expected to meet 1000 times more data traffic demand in the coming decade to support various services such as Augmented Reality (AR), Virtual Reality (VR) for several vertical industries including the automobile industry. The requirements of these vertical industries will be much higher than that of traditional broadband users. The structure of current mobile networks does not allow it to satisfy the diverse requirement of the multifaceted services of the vertical industries as the networks are not scalable and flexible. To satisfy the various requirements in terms of performance, network availability, security, and monetary cost, network slicing has been proposed by various researchers from both academia and industry. The network slicing paradigm has emerged from the well-established virtualization techniques such as Network Function Virtualization (NFV) and Software-Defined Networking (SDN) [1], [2]. The primary concept of network slicing is to divide a physical network into several logical ones which can be assigned for different vertical-specific services. Each sliced part is an isolated virtual network containing several Virtual Network Functions (VNFs) sharing a common physical network infrastructure.

While the core networks can be easily virtualized by utilizing the network slicing technology, slicing of the Radio Access Network (RAN) is quite challenging due to the limited resources [3]. To satisfy the diverse quality of service (QoS) requirements demanded by the individual users, the realization of the RAN slicing needs to be done properly. In traditional RAN, the resources are assigned to several users in a way so that the efficiency of the spectrum sharing is maximized. So, in RAN slicing the primary objective is to allocate the resources among the slice owners in a more flexible and controllable manner so that the resource utilization efficiency is maximized [4]. Slice owners should be given some flexibility so that they can maintain the isolated slices which will prevent the service interruption and improve the utilization of the limited resources. Another challenging issue of RAN slicing is that the resources must be allocated efficiently among the users in real-time [5]. In mobile environments such as vehicular networks, the users move rapidly from one place to another which makes resource management more critical.

Vehicular networks are known for their dynamic characteristics of the node. As the vehicles on the road travel from one place to another with high speed, the users come across various base stations within a short time. Intelligent transportation systems require a high data rate with QoS for the realization of high definition (HD) video streaming, on-demand traffic information, smart navigation, autonomous driving, and several other applications [6]. For emergency applications such as accident reporting, ITS require low latency connectivity between vehicles and the data center. Depending on the purpose and requirements of the application the physical network can be divided into multiple logical units and assigned for user-specific applications. Due to scarcity of resources, while slicing the network, resource management has to be done efficiently so that every user can satisfy their diverse requirements. This paper aims to provide real-time resource scheduling among multiple slices. The limited resources of a base station are scheduled among slices based on the required on-demand services in order to utilize and distribute the resources efficiently while fulfilling the QoS requirements of the service.

The remainder of this paper is as follow. Section II gives the system architecture. Section III discuss about the proposed scheme for scheduling of resources in network slicing. Finally

the conclusion is drawn in Section V.

II. SYSTEM ARCHITECTURE

In this paper, we consider multiple slices deployed on base stations (BS). The BSs are enabled with software-defined Network Function Virtualization (NFV). The physical network is logically abstracted into the sliced layers as shown in Figure . We consider $S_M = \{1, 2, 3, \dots, M\}$ sliced networks. Each sliced network is responsible to meet user requirements. To meet diverse service requirements in terms of bandwidth and latency, the network is sliced specifically considering the constraints. The constraints such as some users require low latency and high reliability, some may require high bandwidth and are not delay-sensitive, and so on. Each sliced or logical network can serve multiple users, likewise, the set $U = \{U_1, U_2, U_3, \dots, U_M\}$ indicates the set of users where $1, 2, 3, \dots, M$ indicates the sliced network. For example, a user watching HD 4K video requires high bandwidth and low latency where an IoT monitoring device may require low bandwidth and high latency can be affordable. Similarly, in [7] experimental evaluation has been done using multiple configurations of virtual radios considering orthogonal frequency division multiplexing (OFDM) and filter bank multicarrier (FBMC) waveform.

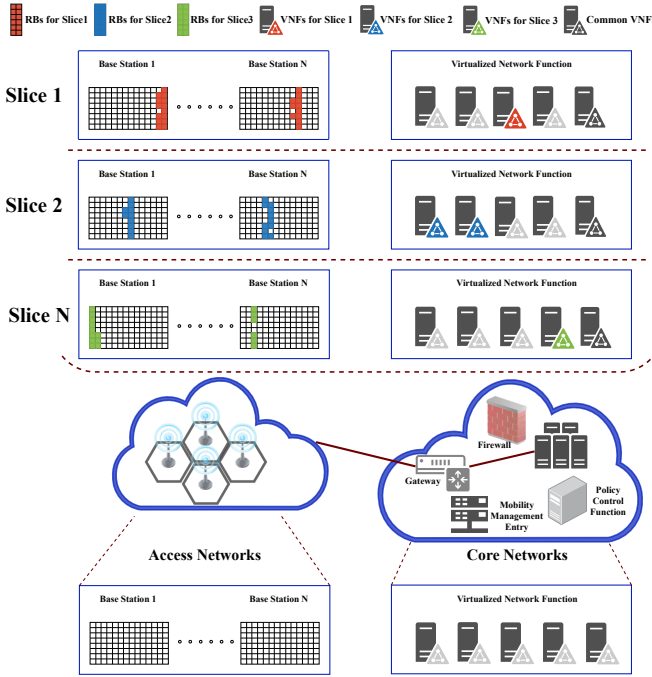


Fig. 1. Resource scheduling in network slicing

III. REINFORCEMENT LEARNING BASED RESOURCE SCHEDULING IN NETWORK SLICING

As the wireless networks evolve, a permanent topic under discussion is resource management that involves, resource allocation and scheduling. In the proposed architecture, different slices are composed of various virtual network functions

(VNFs) and are allocated the required resources. Each slice may cover different BSs and the corresponding resources of the BS are distributed among slices. The slice instances are created based on the diverse service requirements for instance, a slice may require higher bandwidth and lower latency for HD video streaming services whereas for emergency services, high reliability and ultra-low latency may be required. Depending upon the service requirements resources are scheduled among different slices. In the proposed scheme, we use reinforcement learning for real-time scheduling of resources among different slices based on the service requirements. Each BS acts as an agent and performs the actions of scheduling the resources like bandwidth, VNFs, computation resources, etc. to different slices in order to fulfil the quality-of-service (QoS) requirements of that slice. The proposed reinforcement learning model is explained in the following subsection where the states, actions and reward policy are clearly described.

A. Reinforcement Learning

RL based mechanism consists of state and action taken by the agent and in return gets the reward. The BS observes the current state and based on optimal policy takes the action. In order to utilize the limited resources of the BS efficiently, the resources are optimally scheduled among different slice instances on real-time service requirements while maintaining the QoS. For example, if at a particular time instance, only video streaming services are required by the vehicle(s), the BS will allocate most of the bandwidth resources to fulfill the QoS requirements of the video streaming slice. However, in the case when there is some road hazard and emergency message dissemination is to be broadcasted with the images of the hazardous region, priority will be given to ultra-reliable low latency communication (URLLC) slice and the resources will be scheduled to that slice.

The BS acts as an agent and performs the actions of scheduling resources based on the observations of the current state which include the required resources, available resources, and service priority. The service requirements are defined in the service level agreement (SLA) at the time of slice creation. This tells us the required resources by a service. It is represented by R_r . The available resources at the BS are represented as R_a . Finally, the third observation parameter of the state vector, service priority is represented as P . Therefore, the state vector is given by equation 1.

$$S_t = [R_r, R_a, P] \quad (1)$$

Based on the policy, the agent takes an action and gets a reward for the decision made. The BS employs a scheduling algorithm to move the limited available resources among different slices to efficiently utilize the resources. The specific actions are defined based on the scheduling algorithm used. The goal of employing reinforcement learning is to find an optimal policy and maximize the cumulative reward. The reward function is represented by equation 2.

$$R_t = E\left[\sum_{n=0}^{\infty} \beta^n r_t + n\right] \quad (2)$$

where $\beta \in [0, 1]$ is the discount factor.

The stochastic transitions of state and the reward are modeled using the Markov decision process (MDP). The probabilities of rewards and state transitions are dependant on the environment and the decision taken by the agent i.e. action. The conditional transition probability is represented as $P(s_{t+1}, r_t | s_t, a_t)$.

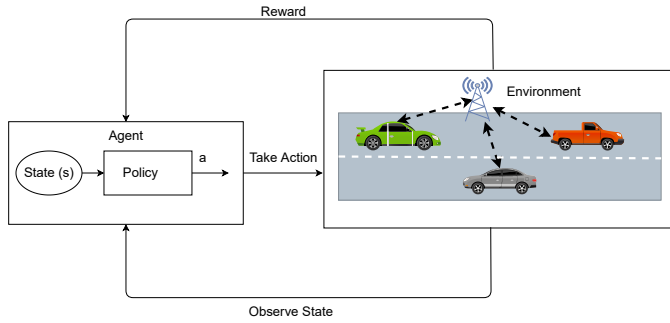


Fig. 2. Reinforcement Learning for resource scheduling in network slicing

IV. ACKNOWLEDGEMENT

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V. CONCLUSIONS

In this paper, we propose a reinforcement learning based scheduling of resources for network slicing in the vehicular network environment. The resources like bandwidth, computation, VNFs, and others are scheduled among the slices providing different services such as video streaming, emergency message dissemination, voice-over-IP, and so on. Since each service and hence each slice has different resource requirements that may change in real-time depending on the demand, the limited resources of the base station are to be managed and scheduled among different network slices. The proposed reinforcement learning based solution provides real-time scheduling of resources among slices for efficient resource utilization while fulfilling the QoS requirements.

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