A Deep Reinforcement Learning based 5G-RAN Slicing Strategy for V2X Services

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***Abstract*— Vehicular communication is a key technology in intelligent transportation systems which links vehicles, roadside units, and pedestrians. One of the key factor for providing design flexibility is Slicing of the Radio Access Network (RAN) which enables 5G systems to support heterogeneous services on one platform through a custom slice for each service. In this regard, this paper provides an overview of an RAN slicing strategy based on Deep Reinforcement Learning (DRL) for a heterogeneous network with two generic 5G services, such as enhanced mobile broadband (eMBB) and vehicle-to-everything (V2X).**

Keywords*— Deep Reinforcement learning (DRL), Network slicing, Radio Access Network (RAN), Vehicle-to-everything (V2X).

I. Introduction

5G is not only an upgrade of wireless technology, but also a transformation of network service architecture. Think back to the three core applications of 5G which are eMBB, mMTC, uRLLC [1]. 5G supports a huge number of connections and extremely low latency, which is the real main difference between 4G and 5G. In other words, 5G's real power lies in building a world where everything is connected. The usage scenarios of mass terminals have ever-changing demands on network speed and latency, and 5G will integrate them into a unified network architecture. In order to cope with the massive network demand, one of the key technologies is 5G network slicing technology [1].

Network slicing is designed to support various applications with different performance and flexibility demands, by splitting the physical network into multiple logical networks [2]. Deep Reinforcement Learning (DRL), through interaction with network, extracts knowledge from experience, dynamically adjusts the resources allocated to each slice, and maximizes resource utilization while ensuring Quality-of-Service (QoS). This paper studies the problem of RAN slicing to provide universal services for 5G, namely V2X [3]. The Reinforcement Learning based strategies for RAN slicing are studied in this paper. The rest of paper is organized as section II explains network model for Radio resource slicing. Section III discusses network slicing strategies for V2X services, including the communications model and network slicing based on reinforcement learning strategy for 5G-V2X services.

II. Network Model for Radio Resource Slicing

Network slicing has gotten a lot of attention from academia and industry as a key technology for 5G. During the slicing deployment phase, the main focus is on resource allocation [2]. This section describes the design details of the resource scheduling scheme, which uses DRL-based dynamic resource scheduling policies to generate resource allocation decisions [3]. The resource status reveals the availability of current resource allocation and usage of each resource that have been scheduled for the slices. Dynamic radio resource management (RRM) schemes adapt radio network parameters to traffic load, user positions, user mobility, QoS requirements, base station density, and other factors. The RAN slice is an isolated End-to-End (E2E) virtualized network that covers all network domains and can be controlled and managed independently on a shared physical infrastructure [2]. As a result, the orchestration of customized slices can be used to provide service across the radio, transport, and core networks, with the help of a slicing framework of dedicated resources [2], [3]. The end-to-end slice profile is designed by splitting the radio resources into two RAN slices by using mechanism of RRM to support eMBB and V2X services respectively. We consider the slice of eMBB is a customized slice that provides service to 5G-V2X based on this concept. We have provided a simple 5G network slice profile in Fig. 1. which utilizes different colors for different services such as eMBB and V2X.

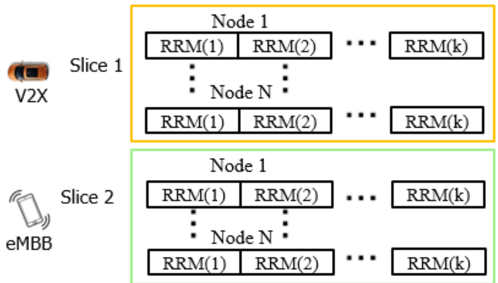

Fig. 1. End-to End slice profile for 5G network.

III. Network Slicing Strategy for V2X Services

A. V2X Communication Model

Cellular Next Generation Radio Access Network (NG-RAN) with gNodeB (gNB) is considered by composing a single cell. This scenario is shown in Fig. 2. [4].

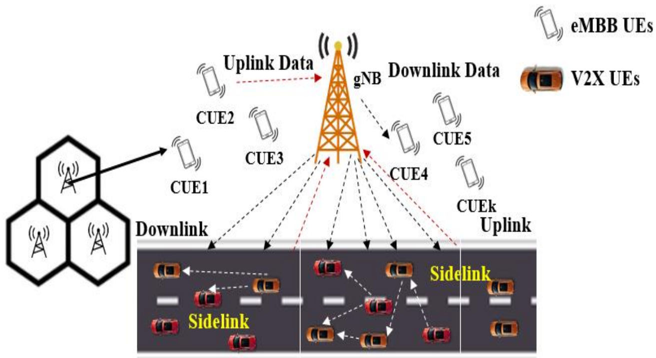

Fig. 2. The cellular network system model with sidelink V2V.

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In above scenario it is assumed that each vehicle includes a CUEs which enables communication between the CUEs in the rest of vehicles in same cluster. The cluster numbers as $j = 1, \ldots, C$; and vehicles in the j-th cluster as $i = 1, \ldots, V(j)$ [3]. Whereas, V2V communication between vehicles can be conducted in cellular or sidelink mode.

V2X services are sensitive to latency, eMBB needs a large bandwidth to support high data rate services, the network is divided into two network slices logically, i.e. the first slice for the V2X services and the second slice for the eMBB services [4]. The bandwidth of the entire cell is organized into Resource Blocks with bandwidth B. N_{UL} denotes the Resource Blocks (RBs) number in the UL, and N_{DL} denotes RBs number in the DL. RAN slicing procedure should distribute the UL and DL RBs to both slices. We can denote $\alpha_{s,UL}$ and $\alpha_{s,DL}$ for representing UL and DL resources, accordingly, for the RAN_slice_ID= s. The slice ratio $\alpha_{s,UL}$ can be divided into two slice ratios [3], [4]:

1) $\bar{\alpha}_{s,UL}$ represents the fraction of UL RBs which are used for uplink transmissions.

2) $\alpha_{s,SL}$ represents the fraction of UL RBs which are used to support sidelink transmissions [3]. (only used by the V2X slice)

$$\textstyle\sum_s \alpha_{s,DL} = 1 \tag{1}$$

$$\textstyle\sum_s \alpha_{s,UL} = \sum_s\left(\alpha_{s,SL} + \bar{\alpha}_{s,UL}\right) = 1 \tag{2}$$

For the eMBB slice (s =2)

$$\bar{\alpha}_{2,UL} = \alpha_{2,UL} \quad where, \alpha_{2,SL} = 0 \tag{3}$$

1. Sidelink mode: transmitting the messages by the SL resources allocated to the slice.
2. Cellular mode: transmitting the messages by the UL and DL resources.

The number of needed RBs from the V2X slice every Transmission Time Interval (TTI): $\tau_{1,UL,}\tau_{1,DL}\tau_{1,SL}$.

$$\tau_{1,x} = \frac{\sum_{t=1}^{T}\sum_{j=1}^{C}\sum_{i=1}^{V(j)} m(j,i,t)*S_m}{\mathrm{T}*SP_{eff,x}*B*F_d} \tag{4}$$

where x represents the type of link, m (j, i, t) denotes the messages number transmitted by the vehicles of the j-th cluster in the t-th TTI, $S_{eff,x}$ denotes the spectral efficiency in the x link, F_d denotes the TTI duration, T denotes TTIs number that defines the time window used to calculate the average [3].

B. DRL based Network Slicing Strategy for V2X Services

Network Slicing is can be carried out by using an offline reinforcement learning approach and then by using a heuristic algorithm [3].

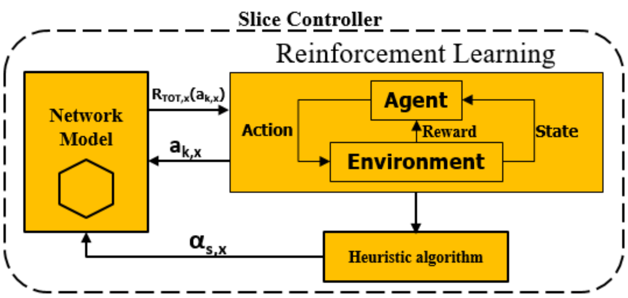

Fig. 3. DRL based RAN slicing strategy.

The above Fig. 3. shows an RL based RAN slicing strategy which works in two stage. In First stage, RL algorithm determines intermediate slicing ratios $\beta_{s,UL}$, $\beta_{s,DL}$ and in second stage a heuristic algorithm takes the results of the RL algorithm as input and adjusts the slicing ratios for the final optimized values $\alpha_{s,UL}$, $\alpha_{s,DL}$.

For UL and DL, the two RL algorithms can be used to determine intermediate slicing ratios $\beta_{s,UL}$, $\beta_{s,DL}$. The optimal solution in an RL-based strategy is based on dynamic interaction with the environment, which is based on trying different actions that are chosen from all of the actions as k=1, ⋯, Ax, where x∈{UL, DL}.The RL procedure is rewarded based on the outcome of the action in terms of the optimization goal [3]. The RL algorithm adjusts the decision-making process as a result of the results, gradually learning the actions and leading to the highest rewards. We will use this study to identify a deep reinforcement-based strategy for 5G network slicing for two important 5G services: eMBB and V2X. In our future research, we will use a deep Q-Learning algorithm, a Markov decision process, and a heuristic approach to achieve network slicing.

IV. CONCLUSIONS

Network slicing is designed to support a variety of emerging applications by dividing the physical network into multiple logical networks with varying performance and flexibility requirements. As per these requirements, we have analyzed the RAN Slicing Strategy for two generic 5G services such as eMBB and V2X based on reinforcement learning and heuristic approach for single heterogeneous network by splitting the radio resources into two RAN slices. In our future research work we intend to work on RL based RAN slicing for uplink, downlink and sidelink communication to provide eMBB and V2X services by using Q-Learning and Markov Decision Process (MDP) based approach.

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